# Bringing economic inequality into coupled economic-environmental models

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This thesis is dedicated to my parents and husband.

# Declaration

This thesis is the result of my own work and includes nothing which is the outcome of work done in collaboration except as declared in the Preface and supplied in the text. It is not substantially the same as any that I have submitted, or, is being concurrently submitted for a degree or diploma or other qualification at the University of Cambridge or any other University or similar institution except as declared in the Preface and specified in the text. I further state that no substantial part of my thesis has already been submitted, or, is being concurrently submitted for any such degree, diploma or other qualification at the University of Cambridge or any other University or similar institution except as declared in the Preface and specified in the text. It does not exceed the prescribed word limit for the relevant Degree Committee.

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# Abstract


Bringing economic inequality into coupled economic-environmental models

Coupled economic-environmental models are cross-disciplinary tools that explore how economic activity interacts with the environment and vice versa. This thesis focuses on models that estimate the economic consequences of climate change, different greenhouse gas emissions pathways, and mitigation efforts. Such models typically examine interactions with gross domestic product (GDP). Within-country inequality rarely features, despite evidence from other disciplines suggesting that climate change may cause significant distributional effects within countries.

The thesis uses input-output analysis (IOA) to explore how climate change may affect within-country income inequality via two case studies. The first uses a prominent integrated assessment model (IAM), the Climate Framework for Uncertainty, Negotiation and Distribution (FUND), to estimate impacts for seven countries, Egypt, Ethiopia, India, Mexico, the United States, Vietnam and Zambia, while the second uses a collection of impact studies for Alaska. Long-term predictions are not feasible for complex, nonlinear systems, so scenario analysis is instead used to explore which sectors, if any, may produce sizeable inequality effects, if results are consistent across countries, if any household groups appear particularly vulnerable, if inequality effects could negate the benefits of average income growth for certain households, and if there is evidence to suggest that poorer or more unequal countries may be more vulnerable to climate change inequality effects. A broad range of types and degrees of climate change costs and benefits are considered. The thesis also reflects on whether income inequality effects are likely to be of sufficient magnitude to merit the increased model complexity or future research focus.


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# List of Acronyms

| | |
|---|---|
| ABMs | Agent-based models |
| AIM | Asia-Pacific Integrated Model |
| BEA | Bureau of Economic Analysis |
| CBA | Cost-benefit analysis |
| CGE | Computable general equilibrium |
| $CO_2$ | Carbon dioxide |
| CPS | Current Population Survey |
| DBEM | Dynamic bioclimate envelope model |
| DICE | Dynamic Integrated Climate-Economy model |
| DSGE | Dynamic stochastic general equilibrium |
| FACE | Free-air concentration enrichment |
| FDI | Foreign direct investment |
| FRED | Federal Reserve Economic Data |
| FRISBEE | Framework of International Strategic Behaviour in Energy and Environment |
| FUND | Climate Framework for Uncertainty, Negotiation and Distribution |
| GARCH | Generalised autoregressive conditional heteroscedasticity |
| GDI | Gross domestic income |
| GDP | Gross domestic product |
| GE | Generalised entropy |
| GHG | Greenhouse gas |
| GLUE | Generalised likelihood uncertainty estimation |
| GMST | Global mean surface temperature |
| GNP | Gross national product |
| HTM | Hamburg Tourism Model |
| IAM | Integrated assessment models |
| IMAGE | Integrated Model to Assess the Global Environment |
| IOA | Input-output analysis |
| IOT | Input-output tables |
| IPCC | Intergovernmental Panel on Climate Change |
| MCMC | Markov chain Monte Carlo |
| MEE | Mixed-endogenous-exogenous |
| MLP | Multi-layer perceptron |
| NAICS | North American Industry Classification System |
| NGOs | Non-governmental organisations |
| NIPAs | National Income and Product Accounts |
| OPEC | Organization of the Petroleum Exporting Countries |
| PAGE | Policy Analysis of the Greenhouse Effect |
| PDFs | Probability density functions |
| RCPs | Representative Concentration Pathways |
| RDM | Robust decision making |
| RICE | Regional Integrated model of Climate and the Economy |
| RMSE | Root mean squared error |
| ROW | Rest of the world |
| SAM | Social Accounting Matrix |
| SCC | Social cost of carbon |
| SCF | Survey of Consumer Finances |

| | |
|---|---|
| SDGs | Sustainable Development Goals |
| SLR | Sea-level rise |
| SNAP | Scenarios Network for Alaska and Arctic Planning |
| SRES | Special Report on Emissions Scenarios |
| SSPs | Shared Socioeconomic Pathways |
| SWF | Social welfare function |
| UK | United Kingdom |
| UNFCCC | United Nations Framework Convention on Climate Change |
| US | United States |
| VSL | Value of statistical life |
| WTA | Willingness to accept compensation |
| WTP | Willingness to pay |

Some paragraphs in Chapters 1 and 3 have been accepted for publication as part of the following forthcoming book chapters:

Prieg, L. F, Yumashev, D., forthcoming. Improving estimates of the economic effects of climate change in integrated assessment models., in: Ninan, K. (Ed.), Environmental Assessments - Scenarios, Modelling and Policy. Edward Elgar Publishing, Cheltenham.

Prieg, L. F., Yumashev, D., forthcoming. Frameworks for dealing with climate and economic uncertainties in integrated assessment models, in: Diemer, A. (Ed.), Integrated Assessment Models and Others Climate Policy Tools:  Challenges and Issues. Oeconomia Editions.

The paragraphs used in Chapters 1 and 3 are the result of my own work. My paper co-author played a supervisory role, and provided comments on these paragraphs. He has approved their inclusion in this thesis.

# Chapter 1 – Introduction

This chapter provides a general background to the topic of the thesis, states the thesis' goals, outlines its contributions, and explains how these fit together to deliver the stated objectives. Section 1.1 details the motivations underlying the thesis. Section 1.2 then introduces the subset of coupled economic-environmental models that are used for the case studies in this thesis, that is, those used to explore the economic consequences of climate change. The section then summarises the history of exploring the economic consequences of climate change, and highlights the within-country income inequality research gap. Section 1.3 outlines the thesis' contributions, including the six research questions that are the main focus of this work. Finally, Section 1.4 describes the individual contributions of the eight subsequent chapters, and explains how the different components of the thesis fit together to deliver the outlined contributions and objectives.

## 1.1 Motivation

People are dependent on their environment for food, water, leisure, shelter and production. Yet social and natural systems are often studied independently. One family of models, however, which this thesis calls 'coupled economic-environmental models', instead explore how economic activity interacts with the environment and vice versa. While such models can address a wide range of questions, this thesis uses those that estimate the economic consequences of climate change, as climate change is arguably the biggest challenge of our generation. The methodology developed, however, could be applied to models that focus elsewhere.

Coupled economic-environmental models typically estimate impacts on gross domestic product (GDP)[1] or production of a specific commodity, and can be global or focused on a specific region(s). Within a region, how effects fall on households existing at different times is also a frequent area of study. There is, however, very limited consideration of how different households in a country at a given point in time could be differently affected, which this thesis calls 'within-country inequality'. Valuable insight may be lost by this approach. For example, if a household in a country enjoys increased income and another household in that country loses the same amount, most coupled economic-environmental models would net these together to conclude there is zero effect, which is obviously an incomplete picture. Similarly, as those on lower incomes generally own a small percentage of a country's wealth, large percentage damages incurred by these households may

[1] Gross domestic product (GDP) is a measure of production defined to be the total value of all the goods and services produced in an economy during one year that are bought by 'final users', i.e. that are not used in further production.

amount to only a small percentage impact on the nation's wealth. The current, modest estimates[2] of the impact of climate change on average incomes could thus be masking severe hardships incurred by some.

Why does inequality matter[3]? Firstly, while the relationship between inequality and growth is currently unclear, they could plausibly interact. Beyond purely economic dynamics, inequality could also cause political instability, regulatory capture, increased crime and moral concerns. Behavioural studies moreover indicate that relative income is a key factor in wellbeing. Finally, the few studies that have explored how climate change may impact on economic inequality have suggested that climate change could cause the poor's incomes to fall while average incomes still rise, so potentially severing the link between GDP growth and poverty reduction[4]. So perhaps ending poverty, reducing inequality, and taking action against climate change, three of the United Nation's Sustainable Development Goals (SDGs)[5], may be interlinked tasks.

One can study inequality without being tied to a 'theory of justice'. This thesis is not focused on the latter, but rather is interested in exploring how climate change damages might be distributed across different income groups, the mechanisms driving such effects, sources of vulnerability, and the consequent trade-offs that climate change and development could entail.

## 1.2 Background

### 1.2.1 Introduction to coupled economic-environmental models

Coupled economic-environmental models are cross-disciplinary tools that are typically built to estimate how environmental change may affect the economy, for example, by exploring global warming or natural resource depletion. Simplifications and trade-offs are unavoidable when combining models of diverse and complex systems. The environmental and economic components of these models, thus, do not reflect the most up-to-date, detailed understanding of their respective subjects. They instead focus on exploring interactions between core processes, which leaves them

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[2] Kompas et al. (2018), for example, estimates that a 3°C increase in global mean surface temperature (GMST) from pre-industrial times will result in a 3% fall in global GDP in 2100.
[3] The following motivations are explored in depth in Chapter 2.
[4] A person is said to be 'poor' if they are living in poverty, i.e. if their family's access to resources is below a given threshold. 'Absolute poverty' is a global metric that indicates an inability to meet basic needs, and is currently generally taken to mean a family income of less than USD 1.90 per day. 'Relative poverty' indicates an inability to meet the living conditions enjoyed by many people in one's country, and the metric can be defined differently in different countries. In the United Kingdom, for example, the threshold is taken to be earning less than 60 percent of the median family income.
[5] In 2015, the United Nations General Assembly set 17 global development goals, called the Sustainable Development Goals (SDGs), to be achieved by 2030. For more information, see https://sustainabledevelopment.un.org.

open to criticism from specialists in both fields who have concerns about the simplification (Rotmans and Van Asselt, 1996).

This thesis focuses on models that explore the economic consequences of climate change, different greenhouse gas (GHG) emissions pathways, and mitigation efforts. These economic-environmental models can broadly be split into two groups. The first contains single-issue studies that are generally microeconomic, where the analysis focuses on one sector of the economy, such as agriculture. For brevity, such research will be called 'impact studies' in this thesis.

The second group draws upon many impact studies to ask broader macroeconomic questions, such as 'how might unabated climate change impact on future GDP'? A prominent subset of models within this group, called Integrated Assessment Models (IAMs) generate plausible and consistent scenarios of future population, economic growth and emissions, with some then using cost-benefit analysis (CBA) to, for example, compare different GHG abatement strategies, or to determine the optimal strategy. Well known IAMs include the Dynamic Integrated Climate-Economy model (DICE) (Nordhaus, 2017) and the Integrated Model to Assess the Global Environment (IMAGE) (van Vuuren et al., 2011).

### 1.2.2 History of exploring the economic consequences of climate change

Scientists started exploring the impact of GHGs on the Earth's climate in the latter half of the 19$^{th}$ century; for example, see Tyndall (1865) and Arrhenius and Holden (1897). It wasn't until the 1960s, however, that the field gained widespread attention with the publication of Pales and Keeling (1965) and Brown and Keeling (1965). These papers introduced the Keeling Curve, which showed that atmospheric carbon dioxide ($CO_2$) concentration had increased since 1957, and so raised the spectre of anthropogenic global warming. It took more time, however, before economists began modelling the economic consequences of climate change, with the topic not being meaningfully explored until the 1970s; for example, see Nordhaus (1977).

In the early days, impact studies were only available for agriculture, energy consumption and sea-level rise (SLR) in the United States (US). There were no studies focused on other regions, so researchers extrapolated from American impact assessments to get estimates for other countries. Early mitigation cost analysis similarly focused on the US; for example, Manne et al. (1990) and Jorgenson (1991).

This American focus can partly be attributed to the US Congress' 1986 decision to ask the US Environmental Protection Agency for a report investigating '*The Potential Effects of Global Climate Change on the United States'* (Smith and Turpak, 1988). It was the first national legislature to take this step, and it produced over fifty academic papers. Data from the resulting study was widely used by subsequent researchers; for example, Nordhaus (1991), Cline (1993) and Fankhauser (1995).

Impact studies for other countries emerged relatively quickly for agriculture and SLR; for example Tobey et al. (1992) and Rijsberman (1991) respectively. Sectors such as forestry, energy, water and health, however, were overlooked for longer. Even in 2000, William Nordhaus, the creator of DICE, reflected that "only agriculture and sea-level change have made significant progress in estimating climate change impacts on a detailed regional level" (Nordhaus and Boyer, 2000). Nearly all studies, moreover, focused on wealthy or very populous countries, such as Canada or China. There was next to no consideration of smaller or lower-income countries (Nordhaus and Boyer, 2000).

Nowadays, global coverage is still sporadic and skewed towards wealthier countries, although some studies for lower-income countries do exist, such as Arndt et al. (2011), Arndt et al. (2012) and Chinowsky et al. (2015) for Ethiopia, Tanzania, and Malawi, Mozambique and Zambia respectively. Similarly, while damages to agriculture and SLR have received more attention than other sectors, studies on forestry, fisheries, energy and infrastructure are now more commonplace; for example, Boccanfuso et al. (2018), Seung and Ianelli (2016), Huang and Gurney (2016) and Melvin et al. (2017) respectively.

Most impact studies and IAMs estimate the interaction between climate, abatement and mitigation efforts, and GDP. Where impacts on different household groups are considered, the focus is typically on the impact of climate change, abatement or mitigation on inter-generational inequality[6] or inter-regional inequality[7]. Intra-regional, particularly within-country inequality rarely features, despite evidence from other disciplines suggesting that climate change may cause significant distributional effects within countries.

## 1.3 Research contributions

A methodology is put forward that extends coupled economic-environmental models so that, in addition to estimating impacts on GDP or production, they can also estimate impacts on within-country income inequality[8]. While this thesis pilots the methodology with models exploring the economic effects of climate change; it could be applied to models exploring other issues.

[6] 'Inter-generational inequality' refers to how households existing at different points in time could be differently affected.
[7] 'Inter-regional inequality' refers to how households in different regions at a given point in time could be differently affected.
[8] As detailed in Chapter 5, inequality ratios, such as Q5/Q1, where Q1 and Q5 are the incomes of the poorest and wealthiest income quintiles respectively, are the chosen measures of income inequality.

Two case studies are then implemented, one for each of the two identified types of coupled economic-environmental models: impact studies and IAMs. The impact studies case study is for Alaska, and is the first multi-sector study of the economic impact of climate change on an Arctic region. The IAM case study uses the prominent IAM the Climate Framework for Uncertainty, Negotiation and Distribution (FUND) (Anthoff and Tol, 2014). These two case studies demonstrate how the proposed methodology is applied, and are also used to address six research questions:

1. Climate change induced changes to which sectors seem likely to have the greatest effect on within-country income inequality?
2. Do impacts to certain sectors consistently increase within-country income inequality across different economies? Or do impacts in some countries reduce inequality and in other countries increase inequality?
3. Do certain household groups seem particularly vulnerable across economies?
4. Is there evidence to support the conclusion in Rozenberg and Hallegatte (2015) that starting levels of average income and within-country income inequality may affect the extent that climate change impacts on inequality?
5. Are within-country income inequality effects relatively small in many or all scenarios compared to projected growth in average incomes? Alternatively, is it possible, as suggested by Dennig et al. (2015) and Rozenberg and Hallegatte (2015), that increased inequality from climate change might cancel out improvements in overall standards of living from GDP growth for low-income households?
6. Is it only in the most extreme climate damage scenarios and time frames that relatively sizable within-country income inequality effects emerge? Or are they plausible in shorter-term, moderate scenarios?

The conclusions drawn from these research questions, along with an analysis of the limitations of the methodology, are then used to consider if the impact of climate change on within-country income inequality is a fruitful area for further research, including whether income inequality effects are too small to merit the trade-off of increased model complexity.

This thesis does not provide definitive answers to the six aforementioned research questions – an implausible goal given the long time-horizon and complex nonlinear nature of climate and economic systems. The aim was instead to start exploring the impact of climate change on within-country income inequality, an area that had hitherto generally been neglected, put forward a methodology to facilitate study, better understand why this question is typically overlooked, and suggest whether the topic should be studied in greater depth, or if instead researchers' time would be better spent elsewhere. The thesis does not, however, investigate how abatement or mitigation may affect income inequality, as many economists already explore the latter[9].

Useful by-products also emerged from this thesis. Firstly, an existing map, called a Social Accounting Matrix (SAM)[10], of monetary flows between different sectors[11] and institutions[12] in an economy, in this case Alaska, had to be adapted so that income inequality effects could be modelled. Other researchers could use this bespoke SAM to explore a wide-range of questions around income inequality in Alaska, such as what types of government investment may most efficiently reduce inequality or benefit the poor.

Similarly, so that a high income country could feature as one of the countries in the IAM case study[13], a SAM specifically set-up to model income inequality effects was constructed from scratch for the US, and will be made available for other researchers to use. Furthermore, a US SAM time-series was generated to empirically test the assumptions underpinning input-output analysis (IOA), the methodology chosen to estimate income inequality effects, and so explore the extent that useful lessons for the future can be drawn from IOA of recent SAMs. This is also a methodological contribution to IOA, as previous work in this area looked only at input-output tables (IOTs)[14], which map a much smaller subset of the network structure of an economy.

Finally, as the US SAMs were constructed from scratch and precise data sources and uses were known, an alternatively disaggregated SAM for 2016 was also produced and used to test the conjecture in Pieters (2010) that disaggregated industry-by-industry labour accounts[15], not just labour accounts disaggregated by, say, educational level, are required to observe differing inequality effects from growth in different sectors. This thesis was, thus, able to make a further methodological contribution to IOA, in terms of the information and model set-up required to enable effective exploration of inequality questions.

[9] As detailed in Chapter 2.
[10] Social accounting matrices (SAMs) are explained in depth in Chapter 4.
[11] 'Sectors' refers to commodities, such as food, wood products and banking services, and economic activities, for example, manufacturing and retail trade.
[12] 'Institutions' means households, enterprises, government and the rest of the world (ROW).
[13] As seen in Chapter 2, existing studies suggest that initial inequality and average income may affect how vulnerable a country is to climate change induced income inequality. It was thus important that the IAM case study used a sample of economies with a wide range of starting inequalities and overall levels of development.
[14] Very few SAM time series currently exist, as compiling SAMs is highly time and data-intensive, whereas IOT time-series are common.
[15] 'Labour' is a 'factor of production', i.e. an input required to produce goods and services that is not itself significantly used-up in production.

## 1.4 Thesis structure

The thesis has nine chapters, including this introductory chapter.

Chapter 2 surveys the existing literature exploring the economic consequences of climate change, and identifies and illustrates the within-country income inequality research gap. A history of economists' evolving attitudes towards income inequality as an economic question is also compiled to help understand why this research area has hitherto often been neglected. This is then considered to establish motivations for filling the research gap. Finally, the preceding analysis is used to develop the six research questions.

Chapter 3 explains the main methodological and subject choices made in this thesis. It starts by introducing coupled economic-environmental models in greater detail and outlines their shortcomings. A discussion of complex systems and decision making under uncertainty forms part of this analysis. In light of this, scenario analysis is then chosen to explore uncertainty, and the scenarios developed for the Intergovernmental Panel on Climate Change (IPCC), which are used in this thesis, are detailed. Alternative modelling procedures for extending coupled economic-environmental models so that they can estimate impacts on within-country income inequality are subsequently presented and contrasted, with the pros and cons of each approach stated and explained. Reflecting on this, the shortcomings of coupled economic-environmental models, and the research questions established in Chapter 2, IOA is identified as the most appropriate modelling approach. In addition, different common ways of measuring inequality are presented, and it is argued that inequality ratios are the most appropriate measure for this thesis. The research questions from Chapter 2 are then used to choose the IAM that will feature in the IAM case study, the seven countries[16] to be explored within this case study, and the region, Alaska, that forms the focus of the impact studies case study. Finally, SAMs for these countries and regions are located.

Suitable SAMs could not be found for Alaska or the United States, so an existing SAM was adapted for the former, while a SAM time-series was constructed from scratch for the latter. Chapter 4 documents these processes.

Chapter 5 introduces IOA, the different forms it takes, and the assumptions it is built upon. The coupling methodology used to incorporate IOA and SAMs into coupled economic-environmental models is then outlined, including the choice of inequality measure. This methodology enables the impact of climate change on within-country income inequality to be explored. Finally, using the time-series of US SAMs constructed in Chapter 4, along with two existing SAM time series, IOA's

[16] The seven countries are Egypt, Ethiopia, India, Mexico, the United States, Vietnam and Zambia.

underlying assumptions are empirically tested, with a reflection on this analysis used to consider the extent that useful lessons for the future can be drawn from an IOA of recent SAMs.

Chapter 6 presents the IAM case study. The model and scenarios are described, as is how regional results were disaggregated to enable sector-level impact estimates for the seven countries featuring in the case study. Using the coupling methodology derived in Chapter 5, within-country income inequality impact estimates for each country are generated across a range of scenarios.

Chapter 7 presents the impact studies case study. The underlying impact studies and scenarios are outlined, and then used with Chapter 5's coupling methodology to estimate within-country income inequality impacts.

Chapter 8 uses the results from the two case studies to address the research questions outlined in Chapter 2. In addition, the sensitivity of results to uncertainty around future economic structure is explored by comparing results generated using different SAMs from the US SAM time-series. Finally, the chapter compares results from the alternatively disaggregated 2016 US SAMs to see if they support the conclusion in Pieters (2010) that disaggregated industry-by-industry labour accounts are required to study differing inequality effects from growth in different sectors.

Chapter 9 summarises this thesis' findings, suggests policy implications, outlines the limitations of the methodology, and draws upon the analysis in Chapter 8 to consider if the impact of climate change on within-country income inequality is a fruitful area for further research, including whether income inequality effects are too small to merit the trade-off of increased model complexity. Finally, areas for future study are suggested.

Figure 1.1 illustrates how the different components of the thesis fit together to deliver the objectives and research contributions outlined in this chapter.

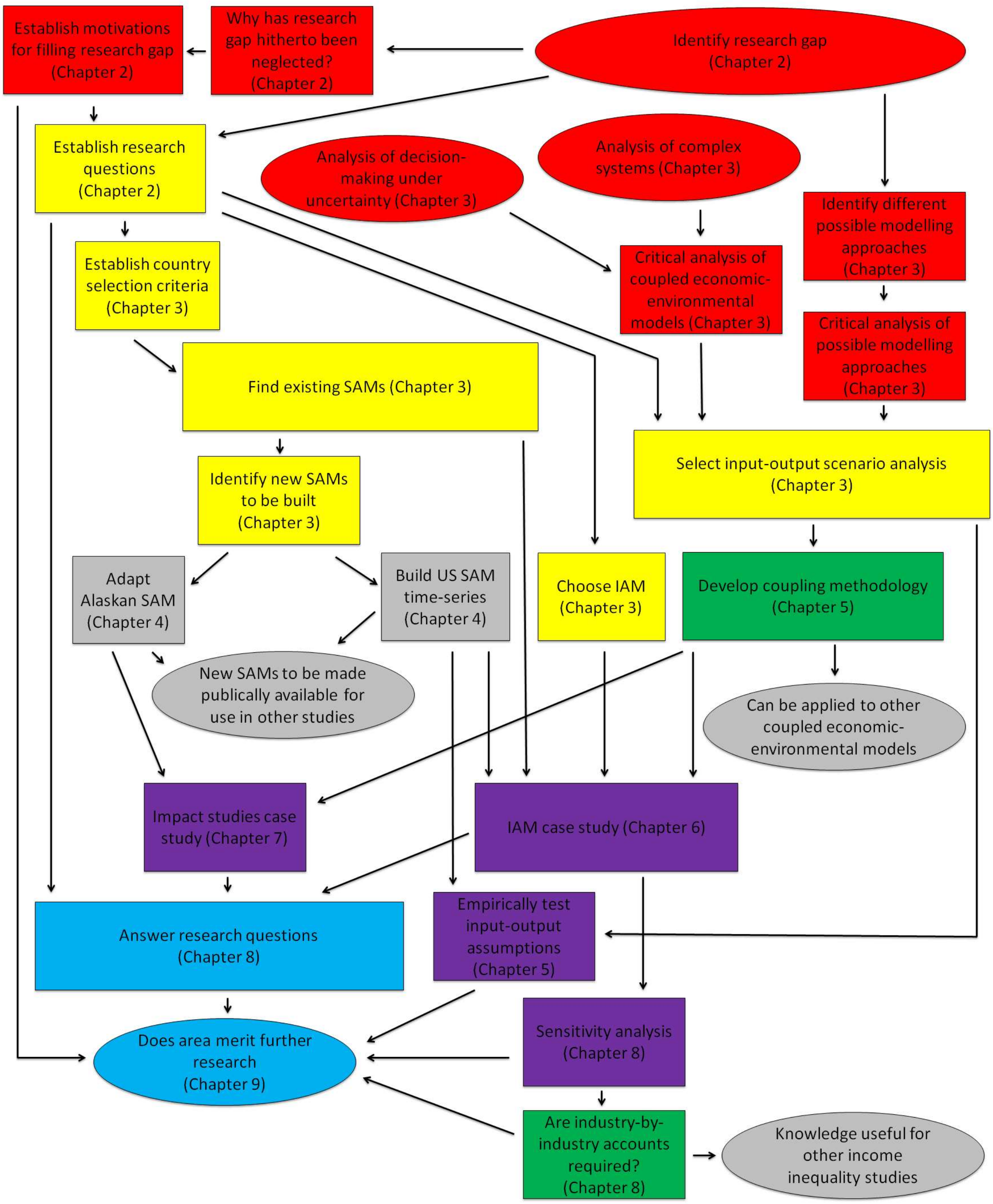
## 1.5 Summary

Coupled economic-environmental models typically estimate impacts on gross domestic product (GDP)[17] or production of a specific commodity, and can be global or focused on a specific region(s). Within a region, how effects fall on households existing at different times is also a frequent area of study. There is, however, very limited consideration of how different households in a country at a given point in time could be differently affected, which this thesis calls 'within-country inequality'.

[17] Gross domestic product (GDP) is a measure of production defined to be the total value of all the goods and services produced in an economy during one year that are bought by 'final users', i.e. that are not used in further production.

This is despite evidence from other disciplines suggesting that climate change may cause significant distributional effects within countries.

Figure 1.1 – Process flow chart




Notes: Diagram illustrates how the different components of the thesis fit together to deliver the objectives and research contributions outlined in Chapter 1. Ovals are start and end points. Rectangles are steps in the process. Red represents a literature review or analysis of a literature review. Yellow represents a methodological choice. Grey represents a useful by-product. Green represents a methodological contribution. Purple represents data generation and analysis. Blue represents a contribution to knowledge.

The thesis explores how climate change damages might be distributed across different income groups, the mechanisms driving such effects, sources of vulnerability, and the consequent trade-offs that climate change and development could entail. It does not aim to definitively answer all questions surrounding climate change and inequality, or even the research questions that formed the focus of this thesis, but it will begin exploration into this complex subject.

Specifically, it puts forward and pilots a methodology that extends coupled economic-environmental models so that, in addition to estimating impacts on GDP or production, they can also estimate impacts on within-country income inequality. The results from two case studies are then used to address six research questions, and to consider if the impact of climate change on within-country income inequality is a fruitful area for further research. Useful by-products were also produced, including a SAM time-series for the US, and a SAM for Alaska that was adapted to enable exploration of inequality questions.

In addition to introducing the thesis' goals and contributions, this chapter also provided background for the thesis. For example, by explaining the two main types of coupled economic-environmental models used in this thesis, impacts studies and IAMs, and briefly summarising the history of exploring the economic consequences of climate change.

Finally, this chapter explained each subsequent chapter's contributions, and how these all fit together to deliver the thesis' goals.

# Chapter 2 – Research gap

This chapter outlines the research gap addressed in this thesis, why it is important that it is filled, and the specific contribution this thesis makes. Section 2.1 of this chapter surveys the existing literature exploring climate change and economic inequality, and notes the lack of research exploring the impact of climate change on within-country income inequality, despite evidence from other disciplines suggesting that different income groups may be differently affected. To help understand why this area has hitherto been generally neglected, a history of economists' evolving attitudes towards inequality as an economic question is then presented in Section 2.2. The preceding analysis is then used in Section 2.3 to establish motivations for filling the research gap, and in Section 2.4 to select the research questions explored in this thesis.

## 2.1 Climate change and inequality

People can be unequal in many different ways. There can be inequality in skills, income, wealth, opportunities, health, and access to rights, education, and healthcare, to name just a few variables. This thesis is focused on income inequality, specifically distribution across households, not how national income is split between land, labour and capital.

Inequalities between different groupings of households have been considered to varying degrees within the literature exploring the economic consequences of climate change, mitigation and emissions abatement. Let us briefly survey the existing work.

### 2.1.1 Existing studies

2.1.1.1 <u>Inter-generational inequality</u>

Inter-generational inequality has received the most attention, primarily due to it being a key feature of cost-benefit analysis (CBA). CBA involves estimating all future costs and benefits, and netting them off against each other to determine total costs or benefits. If the total gains from a project are estimated to exceed the total costs, then the project is deemed an improvement on the status quo. CBA thus requires comparing cash flows that occur at different period of time. This is no easy task, due to the time value of money and human bias to value the present more than the future.

A technique called 'discounting' has been developed, so that all cash flows can be valued as it they occur today. The present value of a future cash flow is defined to be the future value of that cash flow multiplied by a discount factor, $F$, where $F = (1 + R)^{-t}$, and $t$ and $R$ are the years from present day and the annual discount rate respectively. The higher the discount rate, the less weight is placed on future events.

In the integrated assessment literature, the discount factor is typically determined by the Ramsey model (Ramsey, 1928), where $R = \rho + \eta g$. $\rho$ is the pure time preference, i.e. the extent that people care less about the future, $\eta$ is the consumption elasticity[18] of marginal utility of consumption, i.e. the sensitivity of well-being received from an additional unit of consumption to changes in the current level of consumption, and $g$ is the per capita consumption growth rate. The second component of the discount factor, $\eta g$, accounts for future generations being wealthier than the current one, and so being better placed to absorb damages. This means that future impacts count for less when calculating net present values.

A literature review covering research on discounting and intergenerational inequality is presented in Chapter 3, as that chapter also explores the thorny debate surrounding the 'correct' discount rate and the extent that the choice of discount rate affects modelling results. At this point, let's simply note that this is one of the most controversial and unresolved areas of integrated assessment, and a large literature exploring different weightings of the various generations exists, for example Gollier (2013) and Nordhaus (2017). The degree that future generations may be impacted compared to their present counterparts has thus received extensive attention. As part of this, there has also been extensive philosophical debate around the justice of the generations who did not cause global warming being the ones to suffer the impacts; for example, see White (2017).

#### 2.1.1.2 Inter-regional inequality

Even the very early economics of climate change literature recognised that lower-income countries could be more at risk from climate change due to their reliance on agriculture (Fankhauser, 1995). Thus, while the initial models estimating the economic consequence of climate change were global, for example Nordhaus (1991), researchers soon recognised the need to explore the regional, distribution of climate change impacts. These regional estimates corroborated the hypothesis that climate change damages may not be equally distributed across the world. Table 2.1, for example, shows regional damage estimates made using the Regional Integrated model of Climate and the Economy (RICE) (Nordhaus and Boyer, 2000). As a further example, Mendelsohn et al. (2006) explored climate change damages between countries using six scenarios, and finds that the global poor are likely to shoulder "the bulk" of climate change damages, as they live in countries that are already very warm, have large agricultural sectors, and may struggle to adapt.

[18] Elasticity is a measure of sensitivity, specifically the ratio of percentage changes.

Table 2.1 - Regional damage estimates generated by RICE

| **Country or region** | **Damages from 2.5 degrees warming (% of GDP)** |
|---|---|
| India | 4.93 |
| Africa | 3.91 |
| OECD Europe | 2.83 |
| Low income countries | 2.64 |
| Middle income countries | 2.44 |
| High income OPEC countries | 1.95 |
| Global (population weighted) | 1.88 |
| Lower middle income countries | 1.81 |
| Global output weighted | 1.5 |
| Eastern Europe | 0.71 |
| Japan | 0.5 |
| US | 0.45 |
| China | 0.22 |
| Other high income countries | -0.39 |
| Russia | -0.65 |

Notes: Table shows regional damage estimates, as percentages of gross domestic product (GDP), from a 2.5 degrees warming since preindustrial times for different countries and groups of countries. Note than negative damages are benefits. For example, Russia enjoys benefits from warming because its current climate is cooler than the estimated optimal temperature in the region for agriculture and many other affected market sectors, such as forestry, water systems and construction. Russian outdoor leisure time is also expected to increase in a warmer climate, and the monetary value of these nonmarket activities is estimated and counted as additional GDP. All these benefits collectively outweigh expected climate change damages in Russia from, for example, sea-level rise. Damages estimates were generated using RICE, a different IAM to that used for the case study in Chapter 6, and were taken from Nordhaus and Boyer (2000).

As will be described in Chapter 3, Integrated Assessment Models (IAMs) rely on willingness to pay (WTP) and willingness to accept compensation (WTA) methods to value climate change impacts. These valuation procedures, however, will generate different answers depending on the levels of income in the given area. For example, survey participants from richer countries will place a higher monetary value on their environment than their counterparts in lower-income countries (Fankhauser et al., 1997). Market-based valuation methods will also produce higher values for wealthier countries. This all leads to impacts on wealthier countries counting for more than impacts on poorer countries. Some early studies, for example, valued deaths in high-income countries 11.5 times higher than deaths in low-income countries (Risbey et al., 1996).

In the Intergovernmental Panel on Climate Change's (IPCC)[19] early reports, no adjustment was made to address these valuation problems (Fankhauser et al., 1997). Later studies viewed this as unjust, and introduced 'equity weights' that gave greater emphasis to losses or gains incurred by poorer regions, partly to compensate for these valuation inequalities, and partly for broader ethical reasons, such as people in lower-income countries being less able to absorb climate change damages than their wealthier counterparts.

CBA economists have been debating the need for equity weights for decades; for example, see Little and Mirrlees (1968). In particular, equity weights introduce an explicitly normative element to the economic analysis, which many economists reject, as they view value-laden analysis as lying outside the economic discipline. Some researchers also argue that climate change and inequality are separate problems, and should be analysed and solved as such (Fankhauser et al., 1997).

To calculate costs and benefits, the concepts 'utility' and 'social welfare function' (SWF) are often introduced, where utility is a measure of the overall wellbeing of an individual, and a SWF is an aggregation of individual utilities into a social utility that can be used to compare the desirability of different policy options. In the multi-regional RICE, for example, there is a single representative household for each region, so each region has its own utility function and its own SWF, which is the discounted sum of its utility over time.

Utility is difficult to precisely define, let alone measure, so economists frequently take money to be the measuring rod. In IAMs, utility typically depends on consumption, $c$, and it is assumed that utility increases with additional units, but with diminishing marginal utility. In other words, each additional unit of $c$ provides less utility, $U(c)$, than the previous unit, but the utility gained is always positive. Mathematically, $\frac{\partial U(c)}{\partial c} > 0$ and $\frac{\partial^2 U(c)}{\partial c^2} < 0$.This is equivalent to a concave utility curve, i.e. individuals would prefer to be guaranteed a smaller quantity of utility, than to take a gamble and possibly gain more utility but risk having none. The more one values increases in consumption at lower

[19] The Intergovernmental Panel on Climate Change (IPCC) was established by the United Nations in 1988 to compile literature reviews, called 'Assessment Reports', for governments, policy makers and United Nations Framework Convention on Climate Change (UNFCCC). These reports summarise scientific, technical and socioeconomic expertise around anthropogenic climate change and its potential impacts on people, social systems and the natural world.

consumptions levels in comparison to increases in consumption at higher consumptions levels, the more concerned one is about not being at the bottom of the consumption distribution. The concavity of a utility function is thus taken to be an aversion to inequality or a measure of risk aversion, and the more concave a utility function, the greater the risk or inequality aversion. To get a dimensionless measure, one can look at the negative consumption elasticity of marginal utility of consumption, $\eta = -c\frac{\partial^2 U(c)}{\partial c^2}/\frac{\partial U(c)}{\partial c}$. η is a positive constant typically called the coefficient of inequality aversion or relative risk aversion, and estimates of it vary widely from less than 1 to over 10 (Kaplow, 2005), which illustrates how difficult it is to confidently quantify and measure an aversion.

Economists thus don't agree on how households approach risk (Thomas, 2016). A utility function with constant relative risk aversion (CRRA), however, has many useful modelling properties, including that consumption will grow at a constant rate in long-run equilibrium. An isoelastic[20] utility curve is required for CRRA, i.e. for households to invest the same proportion of their wealth in risky assets regardless of their current level of wealth. Only power series utility functions are isoelastic; thus, these are the most commonly used utility functions (Wakker, 2008). They take the format

$$U(c, \eta) = \frac{c^{1-\eta}}{1-\eta} \tag{2.1}$$

where η is constant. Shifting utility by a constant preserves the utility ordering. As IAMs generally assume $\eta \to 1$, this means that $U(c) = \ln(c)$, because

$$\lim_{\eta \to 1} U(c, \eta) - \frac{1}{1-\eta} = \lim_{\eta \to 1} \left(e^{(1-\eta)\ln(c)} - 1\right)/(1-\eta) = \ln(c).$$

RICE, for example, assumes $\eta \to 1$ and so uses the logarithm of consumption for all regions' utility functions (Nordhaus and Boyer, 2000). This means that consumption damages hitting poorer regions will count for more than the same consumption damages hitting wealthier regions. Policy Analysis of the Greenhouse Effect (PAGE) (Hope and Newbery, 2006) and the Climate Framework for Uncertainty, Negotiation and Distribution (FUND) (Anthoff and Tol, 2014a) do not explicitly invoke utility and instead measure impacts directly in terms of changes to gross domestic product (GDP), but implicitly this fulfils the role of a SWF, as the analysis assesses the relative desirability of policies. Furthermore, PAGE equity-weights damages by the factor $\left(\frac{GDP_{f,0}}{GDP_{r,t}}\right)^{\eta}$, where $GDP_{f,0}$ is the initial GDP per capita in a chosen focus region, $f$, and $GDP_{r,t}$ is the GDP per capita in region $r$ at time $t$. This

[20] Isoelastic means that the elasticity, in this case η, is equal to a constant, i.e. η is not a function of either $U$ or $c$.

normalised weighting factor is derived[21] from $(2.1)$. FUND similarly weights each regional 'social cost of carbon'[22] (SCC) by $\left(\frac{GDP_{f,2010}}{GDP_{r,2010}}\right)^{\eta}$, when calculating the global SCC.

As will be shown in Chapter 3, the choice of equity weights can have a large impact on results. Moreover, as the coefficient of relative risk aversion features in both the utility function and the discount rate via $R = \rho + \eta g$, it can increase or decrease SCC estimates depending on whether the discounting effect or equity-weighted utility effect dominates[23]. Chapter 3 explores how this can differ as $\eta$ varies.

The effects of climate change on inter-regional inequality are thus regularly explored using multi-regional Integrated Assessment Models (IAMs), and the impact of introducing equity weights into utility functions has also received significant attention.

In addition, the considerable literature on inter-regional damage inequality has fed into a related debate surrounding inequality of blame and injury between different countries. Wealthier countries are responsible for the vast majority of greenhouse gas emissions. Roberts (2001), for example, observes that "Twenty percent of the world's population is responsible for 63% of the emissions, while the bottom 20 % of the world's people are only releasing 3%". The regions that have contributed least towards global warming, however, may suffer the greatest damages; for example, see Sinivasan (2010). Such countries may also be poorly equipped to absorb damages (IPCC, 2007). This has sparked discussion around how carbon emission rights should be distributed across countries, for example, Alcaraz et al., (2018), and whether wealthier countries should pay compensation to lower-income countries, for example, Tol and Verheyen (2004).

Thus, via exploring equity weighting, how damages may fall differently on different regions, and theories of justice surrounding the latter, the academic community has put considerable effort into exploring interactions between global warming and inter-regional inequality; although some of these problems, such as what are the 'correct' equity weights, are highly contentious. Note that the aforementioned coefficient of inequality aversion is only used when aggregating different utilities, for example, in CBA. As explained in Chapter 3, this project does not use CBA, and so inequality aversion does not feature in this thesis. In addition, as explored in the preceding paragraphs and in Chapter 3, the effect of different equity weighting, including different values of $\eta$, has already been

[21] See Anthoff et al., (2009) for the derivation.
[22] The social cost of carbon (SCC) is the discounted economic impact of emitting an additional tonne of carbon today.
[23] Although one could argue that aversion to inter-regional inequality and aversion to inter-generational inequality are not necessarily equivalent.

extensively explored in the literature.

#### 2.1.1.3 Intra-regional inequality

While inter-generational and inter-regional inequalities have both received much attention, intra-regional inequality, particularly within-country inequality, has been relatively neglected, with multi-regional IAMs, for example, using a representative household for each region.

There are a few, relatively recent exceptions. Anthoff et al. (2009), for example, takes the distribution of average consumption between nations within each region into account in the FUND welfare function. The paper assumes that climate damages fall equally on all individuals, and considers three scenarios for how the consumption distribution may change over time. The first assumes that inequality remains constant, the second that inequality decreases linearly until 2300, when all incomes are equal, and the third that inequality increases at a linear rate until all regions at 2300 are as unequal as the most unequal region in 2000. In the constant inequality scenario, introducing intraregional equity weights into the welfare function is found to increase marginal damages in the IPCC's SRES A1B scenario by 27 – 33%, depending on the pure time preference used. With a 1% pure rate of time preference, the increasing inequality scenario is found to increase marginal damages by a further 55%. The decreasing inequality scenario, in contrast, is found to decrease marginal damages by 19%.

Dennig et al. (2015), meanwhile, considers the income distribution within each region in RICE, and experiments with varying the degree of damages hitting the different income groups. If damages are skewed towards the poor, consumption for those on lower incomes is found to possibly fall as time goes on. It is a widespread conclusion in development policy papers that GDP growth is a key tool to lift people out of poverty, for example Dollar et al. (2016). Dennig et al. (2015) thus raises the possibility that climate change could break this relationship. Dennig et al., (2015) find that the poor's consumption growth in Africa, China and Europe are particularly vulnerable.

Dennig et al. (2015) also observes that if damages are sufficiently skewed towards the poor, then optimal mitigation strategies will change, requiring greater mitigation. Using Nordhaus' usual discount rate, unequal damages could even produce a SCC similar to that found by the Stern Review[24]. As discussed in Chapter 3, the results generated by Nordhaus and Stern greatly differ due to opposing views on discounting. This leads Dennig et al. (2015) to conclude that "properly accounting for the distribution of consumption and damage within regions may be as important for

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[24] The Stern Review on the Economics of Climate Change (Stern, 2007) was a report prepared for the United Kingdom (UK) government by economist Nicholas Stern.

climate policy as the debate over discounting." When damages are proportional to income, however, Dennig et al. (2015) finds that introducing inequality does not change the optimal strategy.

Finally, Dennig et al. (2015) explores what level of flat tax followed by intra-regional transfers on post-damages incomes would reverse the aforementioned change in optimal strategy. Assuming that taxation does not impact on GDP, a 65% consumption tax would be required.

Anthoff and Emmerling (2016) model inequality between nations within RICE-2010 and FUND 3.9 regions by assuming that within-region consumption is log-normally distributed across countries in that region. If climate change damages are skewed towards higher incomes, incorporating *inter*-regional inequality increases the SCC by 167% and 156% in FUND and RICE respectively. Then incorporating *intra*-regional inequality between nations is actually found to reduce the SCC by 12.5% and 3.7% respectively. This is because the welfare functions with equity weights place greater emphasis on those with lower incomes. If damages were skewed towards those on lower incomes, the SCCs would rise. Anthoff and Emmerling (2016) concludes that intra-regional inequality is a 'second-order effect', with inter-regional inequality having a much larger impact on the SCC.

Some non-IAM impact studies have also explored the relationship between climate change and intra-regional economic inequality. Jacoby et al. (2015), for example, uses a general equilibrium model and finds that the effects of a climate-induced food price shock in India would not affect the income distribution if rural wages are adjusted upwards accordingly. Without rural wage changes, however, a food price increase is regressive. Hertel et al. (2010) similarly uses a general equilibrium global trade model to explore climate-induced agricultural productivity shocks in 15 countries in Africa, Asia and Latin America. The study estimates that poverty amongst non-agricultural workers could increase by 50% by 2030 in areas of Africa and Asia. Conversely, poverty rates could fall by 50% amongst agricultural workers in Asia and Latin America. The paper concludes that changes in climate could have "large distributional effects", and so warns against solely relying on aggregate damage estimates. Meanwhile, Havlík et al. (2015) uses a partial equilibrium model, and estimates that by 2030 the effect of global warming on food consumption in a highly unequal world could be double that in a relatively equal one.

Finally, Rozenberg and Hallegatte (2015) uses sector-level damage studies for agriculture, health and natural disasters, and a scenario analysis approach, to explore the possible impact of climate change on poverty in 92 lower-income countries by 2030. Effects are found even in this short time-frame, with the degree of damage varying according to starting levels of average income, inequality, and green policies. As many as 100 million people could be pushed into poverty, and incomes of the bottom 40% could fall by more than 4% in most countries. The bottom 40% in some countries could have their incomes fall by more than 8%. These results are particularly worrying given that the study only considers up to 2030. There is thus a danger that large inequality effects could emerge on even a relatively small time-scale.

In addition, Rozenberg and Hallegatte (2015) finds that with higher starting average incomes and low inequality in lower-income countries, nearly all impacts of climate change on poverty can be eliminated. Impacts on poverty could be 8-12 times higher with lower starting levels of GDP and high inequality. Agriculture and health are the sectors that appear most likely to translate climate damages into poverty.

The few papers exploring the effects of climate change on intra-regional inequality, thus, suggest that these effects could significantly impact on damage estimates, the SCC, and mitigation strategies. Most of the IAM studies, however, explore hypothetical income distributions and damage incidences across income groups, and the non-IAM studies typically focus on agriculture. Rozenberg and Hallegatte (2015) was the first multi-sector study to estimate, rather than assume, inequality effects. However, only three sectors, agriculture, health and natural disasters, were considered in this paper, and no higher-income countries feature.

### 2.1.2 Possible links between climate change and intra-regional inequality

While studies exploring the economic consequences of climate change generally do not consider intra-regional economic inequality, particularly within-country inequality, there is ample evidence to suggest that climate change may affect different people within a region differently. Such studies generally address two themes: ‘exposure’, the extent that people are likely to be impacted by climate change, or ‘resilience’, how easily people can recover when affected. On both metrics, research suggests that poorer people are likely to suffer more from climate change, at least in relative terms.

Firstly, citizens working in agriculture, forestry and fisheries are likely to be more exposed to climate change than people in other professions. Poorer people can be highly dependent on their local ecosystem, including for subsistence farming (Hallegatte et al., 2015). Using data from 24 countries, Noack et al. (2015) found that, on average, 27% of the poor’s income stems from the environment, with the poorest households being most dependent. The study estimates that, in the absence of environmental income, the poverty rate in Sub-Saharan Africa could be nearly 60%.

In a study of 92 countries, Hallegatte et al. (2015) found that the poor are more exposed to climate change induced agricultural shocks. Velazco and Ballester (2016) similarly finds that poor, rural households in developing countries are more exposed to agricultural shocks than their wealthier counterparts. Alem and Soderbom (2010) found the same result for urban households in Ethiopia. In a study of 52 countries, Winsemius et al. (2015) found that poorer people are generally more likely to experience both droughts and extreme temperatures, and Reardon and Taylor (1996) similarly conclude that poorer farmers' crops in Burkina Faso are more affected by drought than their wealthier counterparts, perhaps due to lower quality land and lack of capital.

Food price increases could benefit some of the rural poor, depending on whether they own farms that benefit, or if price rises are passed on to wages. The urban poor, however, do not benefit from high food prices. For example, in a study of the 2010 food price spike, where Thai rice, wheat, sugar, maize, and soybean and palm oil prices rose by 17%, 100%, 64%, 76% and 64% respectively, Ivanic et al. (2012) found that an additional 44 million people in 28 countries fell into poverty.

Inequality effects from climate-induced agricultural damages could emerge even in higher income countries. In the United States (US), for example, households in 2017 earning less than USD 15,000 spent 16% of their total annual expenditure on food, whereas households earning more than USD 150,000 spent only 10% (BLS, 2018a). Similarly, in the United Kingdom (UK), households in 2014 in the lowest income decile spent 16% of their total expenditure on food, while households in the wealthiest decile spent only 8% (ONS, 2015). Household food insecurity is already a serious concern for many low-income groups in high income countries (Loopstra, 2018).

Poor people also often live in areas that are vulnerable to natural disasters, as such locations are typically affordable, and are close to sources of work and income (Hallegatte, 2013; Peacock et al., 2014). In a study of Bangladesh, for example, poorer families were found to be more vulnerable to flooding (Brouwer et al., 2007). In a study of 52 countries, Winsemius et al. (2018) similarly found that those on lower incomes are typically more exposed to droughts and urban floods. Examining 24 countries, Angelsen and Dokken (2018) found that that the poor have greater exposure to weather shocks. Most of the people killed by the 2005 cyclone in Mumbai, for example, lived in the city's slums (De Sherbinin et al., 2007). Even in high-income countries, low-income housing is often poorly made and in more vulnerable locations, thus leaving the properties more exposed to natural disasters (Peacock et al., 2014). When choosing where to live, poorer families do not prioritise avoiding natural disasters (Hallegatte, 2013; Patankar, 2015). While wealthier people also want to locate close to economic opportunities, they can afford to buy property in lower-risk areas.

While the rich may lose more in absolute terms from natural disasters, as they own a large percentage of a country's assets, the poor usually lose a greater percentage of their wealth (Hallegatte et al., 2015; Winsemius et al., 2018). Reardon and Taylor (1996), for example, found that poorer farmers had to sell a greater percentage of their livestock for income in the aftermath of a drought than wealthier farmers, even though the latter sold more in absolute terms.

Negative educational and health impacts from natural disasters are also more likely to affect the poor (Baez et al., 2010), and such effects can be long-lasting (Dercon and Porter, 2014). In an analysis of 92 countries, Hallegatte et al. (2015) found that the poor are more likely to suffer health problems from climate change. In a study of 52 countries, Park et al. (2018) similarly found that the poor tend to be more exposed to heat stress, due to their locations and occupations.

Resilience to climate change damages often depends on existing capital (Huynh and Stringer, 2018). Wealthier farmers may have more capital and technology to enable them to adjust to a changing climate (Jacoby et al., 2015). The poor may also be cut off from financial tools, such as loans and insurance, that can help people adapt to climate change or repair damages (Hallegatte et al., 2015). Reardon and Taylor (1996), for example, found that poorer Burkina Faso farmers had to sell livestock to get income in desperate times. Similarly, 54% of people affected by Huricane Katrina in the United States had no insurance (Ramin and Svoboda, 2009).

Having a diversified income is another crucial component of resilience (Huynh and Stringer, 2018). In a study of before and after a drought in Burkina Faso, the disaster was found to decrease inequality in one region, as farmers had multiple source of incomes and adapted by selling livestock or by migrating and sending back remittances (Reardon and Taylor, 1996). In a different area, however, inequality was found to increase, as the poor were hugely reliant on crop incomes, and struggled to find alternatives. The agricultural industry had also distributed incomes more progressively than other sectors. In general, the poor frequently do not have diversified incomes. In a study of farmers in North-West Selangor, Malaysia, for example, Alam et al. (2017) found that only 20% of farming households contained someone working in a non-agricultural profession, and that only 14% of agricultural household income came from non-agricultural sources. 80% of farmers said that they needed government transfers to successfully adapt to climate change.

Government support for low-income people in the aftermath of natural disasters can also be inadequate (Del Ninno et al., 2003). In Mumbai, for example, government flood assistance payments in response to the extreme floods of 2005 only covered 10-15% of poor families’ lost assets (Patankar, 2015). US government assistance in the aftermath of Hurricane Katrina was also criticised for being slow, and poorly designed and implemented (Kamel, 2012).

It can thus take many years for the poor to rebuild lost assets (Dercon, 2004). In the aftermath of hurricanes Andrew and Galveston in the United States, for example, higher-income areas rebuilt faster than lower-incomes areas (Peacock et al., 2014). Similarly, lower-income Hurricane Katrina victims were more likely to suffer long-term financial difficulties than their wealthier counterparts (Toldson et al., 2011).

Migration is further tool for responding to the income effects of climate change (Reardon and Taylor, 1996). Droughts and tsunamis have caused mass displacement in the past (Marchiori and Schumacher, 2011), although the majority of migrants eventually return to their home. The very poor, however, may struggle to migrate away from affected areas for even a short while (Hallegatte et al., 2015). So this is another aspect of resilience that is frequently beyond their means.

Thus, while studies exploring the economic consequences of climate change generally do not consider intra-regional economic inequality, there is ample evidence from other studies to suggest that climate change may cause significant distributional effects. So why has intra-regional economic inequality been hitherto mostly ignored?

## 2.2 Economists on economic inequality

Economists, from their beginnings to the present day, have been interested in how a society increases the total resources at its disposal, i.e. economic growth (Niehans, 1990). The distribution of these resources, however, has received varying degrees of attention over the years. In addition, certain aspects of distribution, for example, international trade and avoiding monopolies, have consistently held an important place in mainstream economic thought, while other aspects of distribution, particularly the functional and personal income distributions, have moved in and out of focus.

To explore the reasons behind this, let us review how and why economists' attitudes towards studying the personal and functional income distributions have evolved over time. Here the personal income distribution is taken to be the distribution of national income between households, while the functional income distribution is how national income is divided between the different factors of production, i.e. land, labour and capital.

### 2.2.1 Data availability

The data necessary for studying distribution and economic inequality is a relatively new phenomenon. The early economists had very little data at their disposal (Piketty and Goldhammer, 2014). Ricardo and Marx's influential distributional analyses, for example, were not empirical grounded.

The first social accounts were constructed in the late seventeenth century by William Petty (Petty, 1664) and Gregory King (King, 1936). These efforts focused on the UK, although estimates for France were also produced in the late seventeenth century (Le Pesant de Boisguilbert, 1843) and for Russia in the early eighteenth century (Studenski, 1958). This early work generally focused on estimating national income and expenditure, and the breakdown between key constituent parts, such as land-rents and wages. King, in addition, estimated incomes accruing to different social groups, such as lords, knights, merchants, farmers and freeholders, and made international comparisons. By the end of the 19th century, rough social accounts were available for twenty countries thanks to Mulhall (1886). Such early national income estimates were, however, essentially guesswork (Berdell, 2009), and are considered to be highly inaccurate (Piketty and Goldhammer, 2014).

The introduction of the census in 1801 was a key source of more robust national data (Allen, 2018). Similarly, the launch of the modern income tax and accompanying tax returns provided invaluable information (Piketty and Goldhammer, 2014). A new wave of social accounting then took off in the early to mid-twentieth century with Arthur Lyon Bowley in the UK (Bowley, 1937), Simon Kuznets in the US (Kuznets et al., 1941), and Colin Clark (Clark, 1937), who produced data for the UK and Australia, and also introduced the concept of gross national product (GNP)[25].

Although the Gini coefficient, a commonly used measure of inequality, was developed in 1912 by Corrado Gini, reliable estimates of personal inequality were not produced until 1953, when Kuznets developed the first modern estimates of income inequality in an analysis of the US (Piketty and Goldhammer, 2014). It would be decades before such data could be found for a wide variety of countries. The World Bank, for example, only provides Gini coefficient estimates from 1979 onwards, and, for many countries, the data-series begins many years later (World Bank, 2016a).

More recently, Thomas Piketty and colleagues compiled wealth and income inequality data-series for many countries using income and inheritance tax returns; for example, see Atkinson and Piketty (2014). Data on the wealth distribution is, however, still scant, even for many high income countries (Piketty and Goldhammer, 2014).

In this light, it is not surprising that many of the modelling frameworks that arose in economics are highly aggregated (Pasinetti, 2000). Beyond an inheritance of perspectives and methods, however, it does not explain why many contemporary economists are still relatively disinterested in income inequality. For this we must look to other factors.

### 2.2.2 The functional income distribution

Throughout the history of economic thought, when economists refer to ‘distribution’ or ‘distribution

[25] Gross national product (GNP) is the value of all goods and services produced by residents of a country in a year, including the value of goods and services produced by residents abroad, minus the value of goods and services produced in the country by non-residents.

theory' they are almost always referring to the functional income distribution. The early economists who developed this framework viewed land, labour and capital as representing the three main social classes[26] (Aspromourgos, 1996; Kaldor, 1955; Niehans, 1990; Park, 1998).

William Petty is credited with introducing the concept of an economic surplus (Aspromourgos, 1996), equivalent to the output produced that exceeds that required to meet the basic needs of the population. While Petty understood that how this surplus is used will impact on future production, he did not significantly explore this idea (Aspromourgos, 2005). Classical economists, however, became deeply interested in this question (Cohen and Harcourt, 2003; Goodacre, 2014).

A wage–fund doctrine was proposed, where a fixed amount of money from capital was believed to be available for wages, and so, in an analysis that feels Malthusian to a modern reader, salaries became a function of population (Mandler, 2001). If there were too many people, for example, wages would be pushed down below that required for survival, causing the population to fall and wages subsequently to rise.

While Adam Smith developed such a theory of wages, he did not construct a theory of distribution (Sandmo, 2015). He believed that distribution was determined by social institutions and was independent of economic growth (Persky, 1992). David Ricardo, in contrast, believed that distribution between the classes determined all other economic dynamics, including growth and technological progress (Kaldor, 1955). He was concerned, for example, that the corn laws that benefited the British landed gentry would decrease profits and so diminish investment, capital accumulation, and consequently growth (Deane, 1978). It is because of this proposed relationship between distribution and growth, rather than moral reasoning[27], that Ricardo famously declared distribution to be "the principal problem in Political Economy" (Ricardo, 1817).

While Ricardo was interested in distribution as a driver of growth, economist Robert Torrens, along with socialist writers, such as Thomas Hodgskin, and cooperative philosophers, like Pierre-Joseph Proudhon, all pushed for a focus on distribution with the explicit aim of improving conditions for the majority (Deane, 1978; Dobb, 1973). The Industrial Revolution, where returns to capital steadily increased but wages stagnated at a very low level, played a key role in the emergence of this self-conscious socialism (Piketty and Goldhammer, 2014).

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[26] Although it had taken a while for the concept of capital to be developed and profits to be fully distinguished from wages, as capitalism was still in its infancy (Aspromourgos, 1989).

[27] Although one should also note that Ricardo was writing in the decades following the French Revolution, when the power of the British landed gentry and division of the national surplus was being challenged as never before.

Karl Marx, for example, had only a minor interest in growth. He developed theories of unstable growth cycles, where capital-driven growth would lead to crises, followed by more growth, and so on, but he did not work on growth-theory per se. He exhibited no interested in maximising growth, and does not explain what will drive growth in a post-capitalistic society; he merely claims it will be less prone to crisis.

The Classical economists did not, however, emphasise ownership, and, thus, did not develop theories of the personal income distribution (Sandmo, 2015). Questions of ownership were viewed as historical legacies that lay outside of the scope of political economy, as economics was known at the time (Sandmo, 2015)[28]. Thus, while differential rent was considered by Petty and Ricardo, and Smith and Mill explored drivers of wage differences, without a proper consideration of ownership, Classical work could not extend beyond the functional income distribution (Sandmo, 2015).

During the eighteenth and nineteenth centuries, people could approximately be split into landowners, wage-earners and capitalists, and so these bins could be useful representative agents[29]. People nowadays, however, often have more diversified incomes, with workers, for example, also investing via pension funds and sometimes owning buy-to-let properties or enjoying large capital gains from increases in house prices. In such a world, it is harder to draw a parallel between the functional and personal income distributions. The term 'distribution theory', nevertheless, still typically refers to the functional income distribution.

A greater interest in the functional versus the personal income distribution has remained a theme long after the demise of Classical economics, with Jevons, Walker, Cairnes, Marshall, Hicks, Robertson, Debreu, and Arrow, to name just a few, all weighing in on the drivers of the functional income distribution[30]. As Neoclassical economics evolved, however, an interest in even the functional income distribution began to dim.

### 2.2.3 The representative household

A certain degree of aggregation is, of course, necessary in macroeconomic analysis. One does not have the information required to model every consumer and firm in an economy individually, and, even if one did, running such a model would be beyond current computing power. But what degree of aggregation is appropriate?

[28] Although John Stuart Mill believed that the effect of the personal distribution on the economy was relevant to political economy.
[29] People, of course, did not fit perfectly into these categories. There were also, for example, paupers, owner-farmers and a lower middle-class, which included the likes of shopkeepers, tailors and teachers (Allen, 2018).
[30] Excellent summaries of the evolution of distribution theory can be found in Mandler (2001) and Niehans (1990).

Representative agents were formally introduced by Alfred Marshall in the form of a representative firm (Hartley, 1996). Marshall uses it as an abstract concept to justify an industry having a single supply curve, despite firms within a sector being heterogeneous, even if only in size, and so having different marginal costs. The device quickly came under criticism. Piero Sraffa, for example, argued that there is no reason for an industry to have a collective supply curve or for a given price to meet equilibrium conditions for all firms in that industry (Hartley, 1996). Such critiques led to the concept being abandoned in the first half of the twentieth century (Schohl, 1998).

In the 1970s, however, the idea re-emerged in the form of a representative household (Schohl, 1998). A key driver behind this was the newfound desire for macroeconomic models to have microfoundations[31], i.e. for economy-wide phenomenon to be derived from behavioural equations for optimising individuals and firms (Schohl, 1998). If all households in an economy are identical, then the representative household is any household in that economy. Alternatively, if households are not identical, it is equivalent to a pseudo-household whose behaviour matches that of the collective behaviour of all households.

Having a single representative household greatly simplifies the mathematics of solving for general equilibrium (Jarrow and Larsson, 2018). It also circumvents the mathematical issues that could lead to multiple and unstable equilibria (Kirman, 1992). If multiple equilibria could occur, how does one predict which will? The price theory is thus incomplete. Multiple equilibria are also disliked because they make it difficult to definitively rank different policies (Kirman, 1992), an issue that is further discussed later in this chapter. Meanwhile, if equilibria are not stable, this greatly reduces the relevance of general equilibrium theory (Kirman, 1992). Why should one study equilibrium if they are only fleeting, transient states? The representative agent has thus become widespread in Neoclassical models; although most studies that use a representative agent do not justify this choice (Hands, 2017).

There are, however, many questions that cannot be addressed using this framework. Unemployment, for example, cannot be studied under this assumption. Meanwhile, as the representative household both owns and consumes all production, the distribution of income, even the functional distribution of income, becomes unimportant, as all factor income accrues to the same household. Thus, most modern macroeconomic models are not able to explore issues surrounding inequality; although, as will be discussed in Chapter 3, multi-agent macroeconomic

[31] There were concerns that empirical macro-level analyses may produce results that are only valid at a given time and situation, as they may not fully capture causal relationships (Lucas, 1976). In contrast, if one had a model of behaviour at the individual level, this should be able to withstand regime changes.

models have recently become more common.

### 2.2.4 Marginal productivity theory of distribution

The representative agent is not the only reason modern Neoclassical theory has relatively little interest in even the functional income distribution. In the Neoclassical growth model, pioneered by J. B. Clark, and developed by Marshall, Jevons and Walras, marginal productivity determines factor prices and thus the share of income between factors, regardless of how capital, labour and land are initially distributed (Cohen and Harcourt, 2003). Any effects of wages on productivity are overlooked, as is joint-demand for factors. As institutions and other social phenomenon have no impact in this theory, this suggests that the distribution that emerges through market forces is free from political values (Felipe and Fisher, 2003). Many thus see productivity-driven distribution as being ‘fair’.

Assuming perfect competition, the model also predicts that there will be no spare capacity in the economy. All factors, including labour, will be fully utilised, which means there will be no involuntary unemployment (Pasinetti, 2000). If the latter occurs, it is thus the result of interference in the market. Trade union action or introducing a minimum wage, for example, will produce unemployment.

There are many criticisms of the marginal productivity theory of distribution. For example, the theory is built upon the existence of an aggregate production function, which states a recipe for transforming labour and capital into output. While labour and land have units that do not depend on prices, for example, man-hours and acres, measuring aggregate capital and output is more challenging. How can one, for example, add together financial capital and machine capital? The only way to aggregate them is to aggregate their monetary values. Similarly output in the service sector is often not physical, so to aggregate, say, auditing services with asset management services, one must add the financial values of the services provided. Even manufacturing output, which is physical, is heterogeneous and so not easily summed. How does one aggregate the amount of cars and televisions produced, except by financial value? If the price of capital, however, is used to determine the quantity of capital, and this, in turn, is used to estimate the marginal productivity of capital, and thus the price of capital, then one has circular logic. In other words, aggregate output and aggregate capital cannot be defined independently of prices, so these variables shouldn’t be taken to be exogenous in a theory of prices.

Other problems have also been raised, including a non-monotonic relationship between capital intensity and profitability, a phenomenon known as ‘reswitching’ (Moseley, 2015; Osborne and Davidson, 2016), and the ability to empirically test aggregate production functions and marginal productivity theory without instead accidentally testing an accounting identity that will, by definition, always hold (Felipe and McCombie, 2015).

These collective issues, called the 'Cambridge capital controversies', were extensively debated in the 1960s and 70s without resolution, perhaps because an aggregate production function is used to derive many key results in neoclassical economics (Felipe and Fisher, 2003). The marginal productivity theory of distribution is still widely accepted as true[32] and, as a result, alternative theories of the functional income distribution are rarely explored (Felipe and McCombie, 2015). In addition, as the distribution that emerges through market forces is free from political values in this theory, many perceive it as being 'fair', which further impedes interest in inequality.

### 2.2.5 Separation of efficiency and equity

The mathematician Bernoulli introduced the concept of utility, a measure of satisfaction, and first postulated that the benefits gained from additional income decrease as one's starting level of income increases (Bernoulli, 1738). The Marginalist economists later formalised this concept as 'diminishing marginal utility'. It could explain observed phenomena, such as why people consume a greater variety of goods as they get wealthier, and also had modelling appeal as, in the presence of budget constraints, it means that consumption functions have a unique maximum. It could also be used to justify progressive taxation.

With the Marginalist Revolution bringing a newfound attention to the notion of utility, a new branch of economics arose, called 'welfare economics', which aimed to estimate the social well-being stemming from various economic allocation options and so enable different policies to be compared and ranked.

Diminishing marginal utility is a 'cardinal' concept, as it is dependent on a measure of utility where a positive linear transformation would preserve the ordering and the relative spacing between options. Such a measure relies on the existence of a unit of utility, called the 'util'. Unsurprisingly, there are extensive debates between philosophers and economists around how to define 'well-being' (Cartwright and Montuschi, 2014). Similarly, how, practically, can utility be measured? And how could one validly compare the utility experienced by one person with the utility experienced by another?

Many economists started to criticise the use of cardinal utility as an economic tool. Interpersonal utility comparisons, in particular, were deemed too subjective for scientific enquiry. Carl Menger

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[32] For example, it features in nearly all undergraduate microeconomics textbooks (Felipe and McCombie, 2015).

encouraged moving away from attempts to measure utility and instead focused on merely ranking the utilities of different options for an individual. This became known as 'ordinal utility', and diminishing marginal utility is not valid in such a world. Paul Samuelson later proposed that ordinal utility functions could be inferred by observing people's behaviour (Moscati, 2013). This is called 'revealed preference theory'. If people always choose one option over another, for example, than the utility function selected must show a greater level of utility for the preferred option.

Utility here is not interpreted as wellbeing; it is simply a tool that helps explain how people make decisions. Ordinalists, thus, do not explain *why* people make decisions; they model *how* people make decisions. They can still define utility functions for individuals[33]; they just view the numeric difference between utility values at different points on the function as having no meaning. All that matters is that the utility function displays a higher value for more preferred choices. Utility maximisation is, thus, still a valid concept. However, individuals are not necessarily maximising their welfare; they're simply displaying behaviour that is consistent with the chosen function. The analytical emphasis is no longer on well-being but rather on 'preference satisfaction'.

It was found that ordinal utility was sufficient to derive key Neoclassical economic concepts, such as the downward sloping demand curve (Hicks and Allen, 1934a, 1934b). Once it was known that such results could be derived from the extremely weak axiom of ordinal preferences, without reference to cardinal utility, the latter, with its problematic subjectivity, was swiftly dropped from mainstream economics (Kincaid and Ross, 2009). This was the 'Ordinal Revolution'. Most economists were never again to hold cardinality and interpersonal comparisons in high esteem, and without interpersonal comparisons one cannot talk about inequality.

If interpersonal utility comparisons cannot be made, however, how can 'good' policy decisions be determined? Vilfredo Pareto developed a framework, called 'Pareto efficiency' or 'Pareto optimality', which is an allocation of resources such that no one can be made better off without making someone else worse off. It enables the ranking of some economic allocation possibilities above others, without making interpersonal comparisons. Pareto also showed that, if certain conditions are fulfilled, such as perfect competition, all goods are privately owned, and there are no externalities, then general equilibrium points will be Pareto optimal outcomes (Blaug, 2007). This is known as the 'first fundamental theorem of welfare economics'.

While Pareto optimality bypasses interpersonal comparisons, it is difficult to think of changes that do not disadvantage at least one person, unless an economy has spare capacity. Pareto optimality is

[33] Although they often prefer to use indifference curves.

thus of limited practical use. In addition, the situation where one person owns every good and the rest of the population owns none is a Pareto efficient distribution. This surely cannot be considered desirable under any welfare definition, yet Pareto optimality offers no way to determine the relatively desirability of the different possible 'optimal' allocations, as they are 'Pareto non-comparable'. Despite this, welfare economics became centred on this framework. When economists talk about 'efficiency', for example, they are generally referring to Pareto efficiency.

Nicholas Kaldor was troubled by how infrequently Pareto improvements can be found in real life, but suggested that if those who gain from a change could theoretically compensate those who have lost out, then the change should be viewed as increasing economic welfare, as it is a potential Pareto improvement. He believed that economists could safely make such recommendations, and claimed that "the scientific status of [such] prescriptions is unquestionable, provided that the basic postulate of economics, that each individual prefers more to less… is granted" (Kaldor, 1939). Whether or not compensation actually occurs, Kaldor argued, is not an economic question; it is a political issue (Kaldor, 1939). The implication here is that optimising output and questions of distribution are perpendicular issues that can be separated. It's up to the economist to advise how to maximise national income; how this pie is divided is a political decision.

This amendment to Pareto's framework, which became known as 'Kaldor-Hicks efficiency' or the 'hypothetical compensation test', could be applied extensively to real-life problems, and also meant that economists could establish the relatively desirability of many, but not all, Pareto non-comparable policies. The popular policy analysis tool, CBA, for example, ranks policies based on Kaldor-Hicks compensation tests. The latter is a Utilitarian approach, but one that economists claim allows the separation of equity and efficiency as problems (Boadway and Bruce, 1984).

Compensation is, of course, unlikely to occur in reality. How in practice, moreover, could such Kaldor-Hicks improvements be ascertained? Who estimates how much people have gained or lost, and how do they do this? This judgement would fall to economists or central planners, which is very different to the ethos embodied in the fundamental theorems of welfare economics, that individuals acting for themselves in the free market bring about optimal allocations. In addition, the separation of efficiency from equity hinges on distribution having no impact on future growth.

A theory called the 'second fundamental theorem of welfare economics' was developed that suggested exactly this. It was shown that, if certain conditions are fulfilled, any Pareto optimal outcome can be achieved by making appropriate lump-sum transfers and then allowing the free market to steer the economy to general equilibrium. Lump-sum taxes are neutral, i.e. all people are taxed the same amount so, in theory, incentives are not affected. Progressive taxation, thus, is not necessary to move to a different Pareto optimum. Many economists, however, argue that the conditions required for the fundamental theorems of welfare economics to hold are unrealistic (Blaug, 2007). These conditions include perfect competition and no externalities, i.e. all costs are incorporated into the market price. In addition, many query the idea that lump-sum transfers can be practically implemented or that they do not affect incentives (Blaug, 2007).

The belief that efficiency and equity could be dealt with separately was reiterated in another theorem, the Coase Theorem. This states that if property rights can be assigned to correct an externality, for example, by assigning emissions quotas so the market can internalise the cost of pollution, then regardless of how those property rights are initially distributed, a Pareto optimum will be achieved provided transaction costs are zero and there is perfect information.

Coase wrote the paper to illustrate that governments should prioritise minimising transaction costs and defining property rights. He later expressed concern with the frequent interpretation that his paper advocated minimising government intervention when correcting market failures (Hahnel and Sheeran, 2009). Many other economists also criticised the theorem. Paul Samuelson, for example, notes that transaction costs are never zero and, from a game theory approach, there is no guarantee that a Pareto optima will emerge (Samuelson, 1995). He also doubted that the required perfect competition would occur in reality. Nevertheless, the Coase Theorem remains popular and misinterpreted (Hahnel and Sheeran, 2009).

The economic consensus thus became that distribution and efficiency had successfully been separated, with the former falling into the subjective discipline of politics, and the latter being part of objective economics, which had the rigor and prescriptive certainty of the natural sciences. Interpersonal comparisons of utility were deemed obsolete, and key results from economic theory could be derived from ordinal preferences. This school of value-free welfare economics became known as New Welfare Economics.

It emerged as part of a broader debate around what economics was for, where it was postulated that there were two branches of economics, 'positive' and 'normative economics'[34]. Definitions of these words vary, but a common distinction is that positive economics uses the scientific method to determine facts, while normative economics involves both facts and value judgements. This is often

[34] The origins of the positive-normative dichotomy can be traced to David Hume's 'is-ought problem', which notes that it is impossible to logically move from descriptions about the world to statements about how things should be (Reiss, 2017). Hume also asserted that knowledge only consists of facts or logical statements; everything else is opinion, which thus means that ought statements are not knowledge.

expressed as positive economics is the study of 'what there is', whereas normative economics asks 'what ought to be'. By extension, positive economists see economics as the study of economic behaviour, while normative economists think economists should advise on how scare resources are distributed. In his influential essay 'The Methodology of Positive Economics', Milton Friedman, for example, argued "Positive economics… is, or can be, an 'objective' science, in precisely the same sense as any of the physical sciences" (Friedman, 1953). According to Friedman, positive economics can determine "correct" economic policy, and that disagreements about policy arise from a failure to properly separate positive, scientific analysis from normative judgements. Positive economics builds consensus; whereas, with normative economic questions, "men can ultimately only fight" (Friedman, 1953).

New Welfare Economics suggested that a positive economic approach that uses only the scientific method could rank different policies, usually the domain of normative economics, without making subjective 'what ought to be' leaps of logic. This proposition held enormous appeal, and so normative analysis became far less common (Ventura et al., 2016). Economists' rankings of different possible allocations were taken to be 'value-free' and 'scientific', and distribution and well-being were no longer deemed acceptable subjects of economic enquiry, as they could not be addressed scientifically (Deane, 1978).

Not all economists, however, rejected questions of distribution and interpersonal comparison. Abram Bergson, for example, introduced the concept of a social welfare function (SWF), which postulates how individual utilities could be combined to form an aggregate utility function. Such a function requires cardinality. Individuals can also be given different weights in the function. Bergson thus unashamedly proclaimed that welfare economics was normative, and argued that a SWF would "state in precise form the value judgments required for the derivation of the conditions of maximum economic welfare" (Bergson, 1938). Some economists now regularly use SWFs. For example, as discussed earlier, SWFs have been incorporated into CBA.

In addition, some economists became interested in exploring the impact of current distribution on future growth and the impact of current growth on future distribution. After all, economies are dynamic, not static.

### 2.2.6 Interactions between growth and the personal income distribution

Beyond formulating the Pareto efficient framework, at the end of the nineteenth century Pareto also performed one of the first empirical analyses of the personal income distribution. By studying England, Italy, France, Germany and Peru, he found that the distribution of income in these different economies could all reasonably be fit to a specific curve. As these countries had quite different economic systems, Pareto suggested that societies naturally had this pattern of income distribution. This became known as ‘Pareto’s law’. Many people subsequently argued that, if this law is true, redistribution is of limited use, as one cannot significantly alter the income distribution. Progressive taxation could thus reduce national income without reducing inequality, so the only way to increase the poor’s income is for the economy to grow overall. Many economists, however, challenged the empirical basis for this law (Persky, 1992), and nowadays, it is generally agreed that Pareto’s law well describes only the wealthiest tail end of income distributions (Aydiner et al., 2018).

Fifty years later, Simon Kuznets, who had done extensive work compiling national income data, began, like Ricardo, to believe that there was a relationship between growth and distribution, which set him apart from most of his contemporaries[35] (Foster, 2015). Kuznets was particularly interested in the personal income distribution, which had become more accessible thanks to recent advances in national accounting, including Kuznets’ own work. In the 1950s, he proposed that income inequality would increase as a country first develops as, when industrialisation takes place, capital is initially able to exploit the workers who migrate to cities. He then argued that inequality would decrease when development reaches a high enough level to support a welfare state and investment in human capital, such as good state education. If this pattern, called the ‘Kuznets curve’ is true, then growth can be expected to benefit everyone once a country has reached a sufficiently high level of development.

Kuznets, however, derived his theory by looking across countries with different levels of development, instead of following the development of given countries over time. More recent panel data studies typically find no evidence for the Kuznets curve, for example, see (Fields, 2002). In addition, despite many advances in national accounting, Kuznets observed that, with regards to the income distribution, there was still an “unusual scarcity of data” (Kuznets, 1955). He acknowledged that his hypothesis was thus “perhaps 5 per cent empirical information and 95 per cent speculation”. He justifies “building an elaborate structure on such a shaky foundation”, by claiming that

*“[distribution] is central to much of economic analysis and thinking; that our knowledge of it is inadequate… and that so long as [the proposed relationship] is recognized as a collection of hunches calling for further investigation rather than a set of fully tested conclusions, little harm and much good may result… Effective work in this field necessarily calls for a shift from market economics to*

[35] In addition, while Kuznets formalised the modern definition of GDP, he disagreed with the predominant role it then assumed in economics (Kapuria-Foreman and Perlman, 1995), as he didn’t believe it to be a good measure of welfare (EC, 2007).

*political and social economy"*[36] (Kuznets, 1955).

While distribution continued to take a back seat in economics, more economists were starting to think about it. Most arguments suggested, like Pareto and Kuznets, that growth would benefit all income groups. Theories of balanced growth in the long-term, such as those proposed by Robert Solow, for example, suggested that all factors would equally benefit from growth (Piketty and Goldhammer, 2014). Some earlier economists had also made this claim. Léon Walras, say, noted that technological innovation had saved mankind from a Malthusian crisis, and so argued that economic growth had improved conditions for all classes (Sandmo, 2015).

Economists also became interested in heterogeneous individuals. Theories of investment in human capital, for example, emerged to explain productivity differences amongst workers, which were seen to be a key determinant of economic growth (Sandmo, 2015). Milton Friedman, meanwhile, explained the income distribution in terms of differing attitudes towards risk (Sandmo, 2015). In his model, aggregate risk aversion pushes society to implement redistributive insurance policies, whereas societies with a higher collective tolerance for risk will be more unequal.

More recent studies focusing on inequality and growth typically use theoretical axiomatic modelling or empirical regression analysis. Alesina and Rodrik (1994), for example, built a political-economy model that suggests that inequality is bad for future growth, as it prompts greater demand for redistribution, which dampens growth.

When measures of inequality are regressed on growth, a negative correlation between the two is often found (Perotti, 1996). Alesina and Rodrik (1994), for example, found that both inequality of land ownership and income inequality are negatively correlated with growth. Persson and Tabellini (1994) also observed a negative relationship between inequality and subsequent growth. Perotti (1996), meanwhile, in a regression analysis of 67 countries, did not find support for the theory that inequality causes greater demand for redistribution, which retards growth. The study does, however, find that more equal societies have higher levels of education, and thus invest more in human capital, which boosts growth. It also concludes that unequal societies are more politically unstable, which inhibits growth. Forbes (2000), however, suggests that the relationship between

[36] Beyond an interest in the relationship between inequality and growth, Kuznets also had political motivations behind his paper. In the conference during the Cold War where he introduced the curve, he expressed hope that his observations would encourage lower-income countries to stick with capitalism rather than move towards communism (Piketty and Goldhammer, 2014). He was particularly concerned that they would be vulnerable to communist reasoning during the initial increase in inequality that he hypothesised came with development (Kapuria-Foreman and Perlman, 1995).

inequality and economic growth becomes insignificant when country-fixed effects are included in the regression.

An influential development study of 137 high and low income countries over 40 years, Dollar and Kraay (2002) explored growth in average income for the poorest quintile compared to growth in national income. These incomes were found, on average, to rise together. This led the authors to conclude that, in both rich and poor countries, those on the lowest incomes seem to benefit from growth as much as the average person. Hence the conclusion, “growth is good for the poor”[37].

Dollar et al. (2016) notes that while an econometric study may find no average relationship between inequality and growth, in some countries there could be a strong positive relationship between inequality and growth, while in others there could be a strong negative relationship. Ravallion (2005) similarly argued that the relationship between growth and an increase in the lowest incomes may differ depending on which economic sectors drive growth. In a study of Burkina Faso, for example, Reardon and Taylor (1996) observed that the agricultural industry distributed income more progressively than other sectors. Similarly, input-output models[38], which are always disaggregated into many sectors, and often disaggregated into different factors or income groups, have provided another avenue for exploring how growth in different sectors differently affect distribution; for example, Miyazawa (1976) and Pyatt (2001). This sector-by-sector focus, rather than an analysis of aggregates, parallels Kuznets’ approach to studying growth. He understood that certain industries may display higher growth rates than others, and his theories of aggregate growth were thus centred around the different growth rates in different sectors (Syrquin, 2016).

Other studies also indicate that there may not be a fixed law between economic inequality and growth for all countries. Rozenberg and Hallegatte (2015), for example, found that different poverty eradication strategies are needed in different countries, with education and demographic changes being most important in some countries, formal employment in others, and redistribution in yet others. In addition, Gobbin and Rayp (2008) analysed Belgium, the US and Finland and found that a different model for the relationship between economic growth and income inequality emerged for each country. The study concluded that “A country-specific estimation approach is needed since ‘one-size-fits-all’ does not apply in the field of growth empirics”.

This could potentially tie into the ‘varieties of capitalism’ narrative, where whether a country has a liberal market economy or a coordinated market economy affects relationships between a company

[37] Although they acknowledge that this does not necessarily imply that boosting growth is the best or only way to improve conditions for the poor.
[38] Input-output models are described in depth in Chapter 5.

and its employees, labour protection, education and skills acquired on-the-job, a country's comparative advantages, corporate governance, and within-industry collaboration (Hall and Soskice, 2001). Coordinated market economies, for example, tend to have less inequality (Hall and Soskice, 2001).

There are, however, limitations on studies exploring inequality and growth. Firstly, both axiomatic and empirical studies frequently comment on inadequate data. As discussed earlier in this section, wealth data is particularly sparse. There are also concerns about large errors in income distribution estimates. Data from household surveys, for example, are imperfect, particularly with regards to coverage of the very rich (Ravallion, 2001), and even the picture drawn from tax data may be incomplete, due to tax evasion.

Econometrically testing the relationship between inequality and growth is also difficult due to omitted variable bias (Forbes, 2000; Gobbin and Rayp, 2008). A very large number of variables could affect growth, and one has limited degrees of freedom due to the quantity of data points available. Introducing dummy variables for time-fixed and country-fixed effects can reduce this problem. Lagged regressors, however, are often believed to be needed, which can compromise the consistency of time-fixed estimators. Panel data dynamic models, such as *Generalised Method of Moments* (GMM), have also been tried; however, problems can still persist depending on the extent of autoregression (Gobbin and Rayp, 2008). Simultaneous causality is also an issue, and it is difficult to identify adequate instrumental variables.

In short, those studies that have explored the relationship between growth and the personal income distribution have found mixed results, with some finding positive or negative relationships, and others finding no relationship at all. Some even suggest that there is no fixed 'law' between inequality and growth across countries, and that different countries exhibit different relationships. Which sectors drive growth may be a key factor behind the latter. Neves et al. (2016) provides of summary of the widely different estimates of the relationship between inequality and growth that can be found in the literature. All these studies are, however, inhibited by lingering problems with data availability, along with possible omitted variable bias and simultaneous causality.

### 2.2.7 Summary

Distribution theory is typically focused on the functional income distribution, despite people no longer being easily split between the traditional classes, land-owners, capitalists and workers. Despite a lack of data, the Classical economists, particularly Ricardo, were highly interested in how distribution affects growth. In the Neoclassical model, however, the impact of distribution on future growth and the impact of initial endowments are not considered, beyond asserting that interfering with market processes will cause unemployment and impede growth. As the distribution that emerges through market forces is determined by the marginal productivity of factors, it is thus often viewed as being value-free or even 'fair'. With the commonly used representative household, moreover, distribution became truly unimportant as, under this assumption, all national income accrues to one individual. One cannot study inequality using such a framework.

Following the Ordinal Revolution, it has become unpopular to make interpersonal comparisons or to explicitly bring value-judgements into economic analysis. Kaldor-Hicks compensation tests and the fundamental theorems of welfare economics were believed to have shown that questions of efficiency and distribution could be separated, with the former studied scientifically by economists and the latter appraised using political values. This implied that a positive economic approach could be used to rank policies, and also explains why economists have remained interested in inter-country inequality, as politicians can address domestic inequality via fiscal policy, whereas large fiscal flows across countries do not occur. The assumptions underpinning such proofs, however, are unrealistic and reflect prioritising an ability to solve for a single general equilibrium solution, i.e. mathematic elegance, above realism. Without these assumptions, Neoclassical theories of distribution, including marginal productivity theory, do not hold.

Not all economists, however, rejected questions of distribution. SWFs, for example, began to be incorporated into models, including CBA. Additionally, some economists began, like Ricardo, to believe that there was a relationship between the income distribution and growth. Early empirical analysis by Pareto and Kuznets, for example, along with axiomatic balanced growth models, suggested that "a high tide lifts all boats".

Data availability has, historically, severely limited studies of distribution, and there are unfortunately still problems with a lack of data, particularly with regards to the wealth distribution. In addition, empirical analyses of the relationship between growth and the personal income distribution likely suffer from omitted variable bias and simultaneous causality.

Recent empirical studies, nevertheless, have been attempted, and have found mixed results, with some suggesting positive or negative relationships between growth and the personal income distribution, while others find no relationship at all. These varying conclusions are perhaps indicative of the aforementioned statistical issues. There may also not be a fixed 'law' between inequality and growth, with the relationship differing across countries depending, say, on institutional factors and which sectors drive growth.

While the relationship between inequality and growth is currently unclear, there are many plausible potential causes of such interactions. Firstly, the demand for redistribution may affect incentives and reduce growth. There are also administrative costs associated with redistribution. High levels of inequality can additionally encourage debt-fuelled consumption by households in a bid to “keep up with the Joneses”, and so lead to financial instability (Cardaci, 2018). While increased inequality may facilitate saving and investment, if these savings are invested in the international capital markets, as the wealthier members of society often do when they save, this may not improve a country’s long-term growth prospects. In contrast, additional money received by those on lower incomes, who save less, could have greater domestic multiplier effects to boost aggregate demand.

Beyond purely economic dynamics, inequality could also cause political instability, which is bad for investment and growth (Perotti, 1994). Similarly it could lead to regulatory capture, resources wasted on lobbying, and ‘rent-seeking’[39], as the wealthy may exert disproportionate influence over the political process (Stiglitz, 2013). Such behaviour can severely impair economic efficiency. Low tax rates also necessitate lower public spending on, say, public health and education, which are key to developing human capital, a driver of growth. Economic mobility could also be affected. Low public spending, for example, can produce poverty traps that last for generations (Perotti, 1996). In addition, there could be underinvestment in research, infrastructure and tackling crime, making it more difficult to do business.

Finally, the value of money itself, and thus prices, will be affected by distribution. In an economy where one person has all the income, for example, the concept of money itself would likely break down. So not only is growth potentially affected by inequality, the measuring rod itself is.

In countries where there is a relationship between inequality and growth, the idea that these two issues can be treated separately falls apart. Thus, as our understanding of the dynamics between growth and inequality improves, economists may have to address efficiency and distribution together, and explore the possibility that there may not be an objective, value-free way to rank policies.

## 2.3 Motivation for thesis

As this chapter has shown, economists estimating the economic consequences of climate change have extensively considered problems of inter-generational and inter-regional economic inequality, yet intra-regional economic inequality, particularly within-country inequality, is rarely considered, despite ample evidence from other studies to suggest that climate change may cause significant

[39] Rent-seeking is any activity that increases one’s share of national income without increasing national income, i.e. wealth transfers without wealth creation.

distributional effects. This is likely partially due to the deep uncertainties surrounding estimates of the economic damages from climate change, which will be explored in Chapter 3. When modelling processes are already so uncertain, to introduce further uncertainties one should be confident that additional complexity is adding value. The absence of thought on within-country inequality, however, is also consistent with the trend in economics over the past seventy years to believe that national distribution is a political question that lies outside the scope of economics.

This thesis will focus on within-country income inequality. As has been explored, while the relationship between inequality and growth in a country is currently uncertain, there are many plausible causal links to suggest that inequality may impact on growth, and vice versa. If these links prove true, then growth and inequality may need to be addressed simultaneously rather than via separate sets of policies. In addition, Dennig et al. (2015) suggests that large tax increases could be required to reverse climate change inequality effects. This could be difficult politically, so, even if inequality has no impact on growth, this weakens the idea that climate change and inequality are separate problems that can be solved in isolation from one another, and that fiscal policy could easily be used to correct any distributional impacts from climate change.

Beyond economic concerns, how climate change may impact on economic inequality is also of interest from social and political perspectives. Behavioural studies, for example, indicate that relative income is a key factor in wellbeing (Stiglitz, 2013). Income inequality is also correlated with crime (Metz and Burdina, 2018) and conflict (Bartusevičius, 2014).

Amartya Sen argues that all political, ethical and economic ideologies are interested in equality, but disagree on “equality of what?” (Sen, 2010). For example, communists value equal wealth, whereas classical Utilitarians value all individuals being given equal weight in any social calculus. Similarly, Libertarians believe that all people should have complete autonomy and freedom. Thus distributive justice seems to feature in some form in all major theories of social organisation. ‘Fairness’ appears to be a core human value; we just don’t all agree on what it means.

As has been shown, in recent decades, there has been a belief in economics that growth in average income benefits those on the lowest incomes. This is consistent with John Rawls’ philosophy that inequalities are permissible if they benefit the least endowed (Rawls, 1971). Dennig et al. (2015) and Rozenberg and Hallegatte (2015), however, suggest that climate change could cause the poor’s incomes to fall while average incomes rise, so potentially severing the link between GDP growth and poverty reduction. The results in Rozenberg and Hallegatte (2015) suggest that this could occur as early as 2030. So perhaps a rising tide may no longer lift all boats, and poverty reduction and tackling climate change may be interlinked tasks. As the poor own a small percentage of a country’s wealth, large percentage damages incurred by those on lower incomes may amount to only a small percentage impact on the nation's wealth. The current, modest estimates of the impact of climate change on average incomes could thus be masking the severe hardships incurred by some. So even if inequality does not affect growth, economists may be forced to operate in a world of trade-offs, where 'optimal' policies cannot be declared without making explicit value-judgements.

For IAMs with equity weights, if climate change damages are skewed across the income distribution then the SCC could be quite different to current estimates, which could also impact on recommended mitigation strategies. Dennig et al. (2015) even suggests that the magnitude of such effects could be comparable to the issues surrounding discounting; although Anthoff and Emmerling (2016) concludes that intra-regional inequality effects are smaller than inter-regional inequality effects. For reasons explored in Chapter 3, this thesis is not concerned with how estimates of the SCC are impacted. This, however, could be of interest to other researchers, and the results of this study could be used to improve current approaches, which, as we have seen, typically rely on speculative skews of damages across income groups, instead of formal modelling of how damages might be distributed.

## 2.4 Research questions

There are two main components of economic inequality, income and wealth[40], which can compensate for each other. Wealth, in the form of housing or other financial assets, could be sold, for example, if the owner suffers a loss of regular income. In addition, holding wealth in the form of, say, shares and bonds, generates an income stream without needing to sell. There is ample evidence, as documented in Section 2.1.2, that climate change could have a large impact on stocks of wealth which could, in turn, could produce distributional effects. Unfortunately, as noted in Section 2.2.1, data on the distribution of wealth is currently sparse, even for many high income countries. It thus was not feasible to include wealth in this study, so this thesis focuses only on within-country income inequality. One should remember, however, that only one facet of economic inequality is being explored.

Firstly, to incorporate the hypothesis outlined in Section 2.2.6 that inequality effects from changes to growth may vary depending on which sector is driving these changes, this thesis will explore whether climate change impacts to different economic sectors have different effects on inequality.

[40] Wealth is the stock of total assets held at a given point in time, whereas income is money received over a given period of time, usually a year.

Specifically, the first research question addressed in this thesis is

1. Climate change induced changes to which sectors seem likely to have the greatest effect on within-country income inequality?

To probe another conjecture from Section 2.2.6, that the relationship between growth in a sector and inequality may vary across countries, the thesis' second research question will be

2. Do impacts to certain sectors consistently increase within-country income inequality across different economies? Or do impacts in some countries reduce inequality and in other countries increase inequality?

The literature review in Section 2.1.2 suggests that climate change may affect different people within a country differently, but whether it is the poorer or wealthier members of society that are most affected may vary from country to country depending on, for example, the poor's dependence on ecosystems, if food price rises are passed on to agricultural wages, government insurance schemes, state healthcare, which sectors are most impacted by climate change, if climate change affects the financial system, etc. The third question asked in this thesis is thus

3. Do certain household groups seem particularly vulnerable across economies?

As outlined in Section 2.1.1.3, Rozenberg and Hallegatte (2015) found that with higher initial starting incomes and low-inequality in lower-income countries, nearly all of climate change's impacts on poverty may be eliminated. This thesis thus asks

4. Is there evidence to support the conclusion in Rozenberg and Hallegatte (2015) that starting levels of average income and within-country income inequality may affect the extent that climate change impacts on inequality?

Similarly, as Dennig et al. (2015) and Rozenberg and Hallegatte (2015) raise the possibility that climate change could sever the relationship between rising average incomes and increased incomes for the poor, this thesis asks

5. Are within-country income inequality effects relatively small in many or all scenarios compared to projected growth in average incomes? Alternatively, is it possible, as suggested by Dennig et al. (2015) and Rozenberg and Hallegatte (2015), that increased inequality from climate change might cancel out improvements in overall standards of living from GDP growth for low-income households?

Finally, Rozenberg and Hallegatte (2015) found that notable inequality effects emerged on a relatively short time-scale – by 2030, so the final question explored in this thesis is

6. Is it only in the most extreme climate damage scenarios and time frames that relatively sizable within-country income inequality effects emerge? Or are they plausible in shorter-term, moderate scenarios?

## 2.5 Summary

This chapter explored the existing literature on climate change and inequality, and observed that such studies typically feature inter-generational inequality and inter-regional inequality. Intra-regional inequality, particularly within-country inequality, typically is not present, and, where it is, hypothetical income and impacts distributions are generally used. For example, only one study could be found that estimated, rather than assumed, the distribution of effects, and this paper only considered three economic sectors and did not feature higher-income countries. Many studies from other disciplines, however, suggest that climate change is unlikely to equally impact different income groups.

To help understand why within-country inequality is so often overlooked in the coupled economic-environmental models that explore the economic consequences of climate change, a history of economists evolving attitudes towards inequality as an economic question was then compiled. This found that distribution theory is often solely focused on the functional income distribution, despite people no longer fitting easily into labour, capitalist and landowner classes thanks to the rise of extremely high wages for some, and many people both working and owning, say, shares and buy-to-let properties. The dominance of Neoclassical economic theory was found to be another key factor, as this approach advocates the marginal productivity theory of distribution, so distribution may be viewed as being 'fair', and frequently uses a single representative household, which means that inequality cannot be modelled. Furthermore, the ordinal revolution, along with the second fundamental theory of welfare economics and Coase's theorem, gave the impression that questions of economic growth and distribution could be separated, which suggested that economics could be a 'positive', value-free discipline like the natural sciences. Nevertheless, some economists, such as those doing CBA using SWFs, and input-output analysis with disaggregated household models, continued to take an interest in distribution. As data availability improved, empirical analysis of growth and distribution also emerged. While early work by Pareto and Kuznets suggested that "a high tide lifts all boats", later work paints a less clear picture, with some studies finding a positive relationship between growth and inequality, some a negative relationship, and others no relationship at all. This has led some to conclude that the relationship might differ from country to country depending on, for example, institutional factors and which sector is driving growth. Work in this contentious area continues, and still suffers from data limitations along with statistical challenges, such as simultaneous causality.

While the relationship between inequality and growth is currently unclear, there are many plausible interactions. Beyond economic considerations, inequality could also cause political instability, regulatory capture, resources wasted on lobbying, reduced well-being, increased crime and poorer health outcomes. Distributive justice also seems to feature in some form in all major theories of social organisation, and so ‘fairness’ appears to be a core human value.

Having established the research gap, explored why it has arisen, and outlined motivations for filling it, this chapter then set out the six research questions that are explored in this thesis, and described how they arose out of the proceeding analysis. Finally, this chapter highlighted that this thesis only explores one facet of within-country inequality, income inequality, as wealth inequality could not be included due to data limitations.

Thus, henceforth in this thesis, ‘inequality’ is taken to mean within-country income inequality, unless otherwise stated.

# Chapter 3 – Choice of methodology and case studies

This chapter explains the main methodological and subject choices made in this thesis. Section 3.1 of this chapter introduces integrated assessment models (IAMs) in greater depth, including the different types of IAMs and common criticisms of this family of models. This includes discussions about the impossibility of testing counterfactuals, difficulties in modelling and predicting complex nonlinear systems, and if and how imperfect models can still be useful. Section 3.2 outlines alternative frameworks to cost-benefit analysis (CBA) that are specifically developed for dealing with high levels of uncertainty. One of these approaches, scenario analysis, is then selected for exploring uncertainty in this thesis, and the scenarios developed for the Intergovernmental Panel on Climate Change (IPCC), which are used in the case studies in this thesis, are then detailed. Section 3.3 reviews the main tools currently used for macroeconomic modelling, their varying strengths and weaknesses, and then uses these, along with a consideration of the research questions outlined in Chapter 2, to argue that input-output analysis is the most appropriate tool for bringing economic inequality into coupled economic-environmental models. Section 3.4 discusses the common ways inequality is measured, and explains which measures will be used in this thesis. The choice of IAM for the case study in Chapter 6, along with the seven countries that are studied in the case study, is then justified in Section 3.5. Finally, the choice of region for the impact studies case study in Chapter 7 is detailed in Section 3.6.

## 3.1 Introduction to IAMs

### 3.1.1 Different types of IAMs

As described in Chapter 1, IAMs are cross-disciplinary tools that explore how economic activity interacts with the environment and vice versa. IAMs can have different goals. One set of IAMs, for example, derives scenarios for different demographic, economic and technological futures and associated greenhouse gas (GHG) emissions trajectories, and explores impacts on climate variables and the biosphere. Prominent IAMs in this group include the Asia-Pacific Integrated Model (AIM) (Masui et al., 2011), the Integrated Model to Assess the Global Environment (IMAGE) (van Vuuren et al., 2011b) and the Model for Energy Supply Strategy Alternatives and their General Environmental Impact (MESSAGE) (Riahi et al., 2011). These IAMs tend to be large, complex and computationally intensive. As a result, they are typically deterministic, as these models involve thousands of parameters that often have unknown probability density functions (PDFs)[41]. In addition, even if the PDFs were known, computational power is often not sufficient to run large numbers of simulations with varying parameters.

A separate set of IAMs aims to estimate the economic consequences of different GHG emissions trajectories and adaptation strategies. These IAMs tend to be much smaller and simpler, which means that uncertainties can be explored using Monte Carlo analysis[42]; although some IAMs in this category are deterministic. These models either generate plausible and consistent scenarios of future population, economic growth and emissions themselves, or use the scenarios produced by the previous set of IAMs as exogenous inputs, and then generate their own estimates of subsequent changes in global mean surface temperature (GMST) and sea-level rise (SLR), along with associated economic costs and benefits. They typically use CBA to compare different GHG abatement strategies, or to determine the cost-optimal strategy. Well known IAMs in this category include the Dynamic Integrated Climate-Economy model (DICE) (Nordhaus, 2017), the Climate Framework for Uncertainty, Negotiation and Distribution (FUND) (Anthoff and Tol, 2014a) and Policy Analysis of the Greenhouse Effect (PAGE) (Hope, 2013). These models can be global or multi-region. DICE, for example, is a global model, whereas FUND and PAGE estimate regional damages, with 16 and 8 regions respectively.

This second group of IAMs will often focus on estimating the 'social cost of carbon' (SCC), which is the discounted[43] costs net benefits of emitting an additional tonne of carbon today. William Nordhaus, the creator of DICE, for example, called the SCC "The most important single economic concept in the economics of climate change" (Nordhaus, 2017). The SCC is calculated by running the same climate and socioeconomic scenario twice, typically a 'business as usual' scenario; only, in one case, assuming additional carbon dioxide ($CO_2$) emissions in the starting period. The SCC will, thus, be different for different scenarios; although the variation is often limited (Hope and Newbery, 2006). With recognition of its limitations, the SCC is sometimes cautiously put forward as the possible tax that should be applied on carbon emissions to correct for associated climate change 'externalities', i.e. costs from carbon emissions not being included in the prices of goods and services produced by carbon-emitting industries. For example, see Anthoff and Tol (2013) and Hope and

[41] Probability density functions (PDFs) capture the relative likelihoods of the different values that a given parameter might take.

[42] In Monte Carlo analysis, one estimates or assumes the range of plausible forms or values that, respectively, equations and parameters may take, and also the associated PDFs, which capture the relative likelihood of the different options. Many simulations are then run where the model is varied in accordance with the PDFs, so that one can explore how model outcomes are affected by model uncertainties.

[43] See Chapter 2 for a description of discounting.

Newbery (2006).

This thesis is interested in how climate change may impact on economic inequality, and so focuses on IAMs in the second category. As discussed, these models specialise in estimating the economic impacts of changes in climate variables, whereas IAMs in the first category focus on how different demographic and socioeconomic futures change GHG concentrations trajectories, and then how the latter impact on climate variables and the biosphere. They are, thus, less appropriate for addressing the research questions outlined in Chapter 2.

### 3.1.2 Criticisms of IAMs

Much of the criticism of the second category of IAMs revolves around their use of CBA; although their damage functions, treatment of uncertainties, and levels of transparency are also frequently challenged. Let us briefly examine these common critiques in turn.

#### 3.1.2.1 Discounting

As described in Chapter 2, CBA involves aggregating the costs and benefits of a project over time into a net present value. This requires comparing cash flows that occur at different periods in time using a process called ‘discounting’.

Table 3.1 – Estimated 2020 SCCs (in USD per tonne of carbon) using different IAMs and discount rates

| | **Annual discount rate** | | |
|---|---|---|---|
| | **5%** | **3%** | **2.5%** |
| **DICE** | 12 | 40 | 59 |
| **PAGE** | 23 | 74 | 105 |
| **FUND** | 3 | 22 | 37 |

Notes: Table shows how the social cost of carbon (SCC) varies when using three different annual discount rates and three different integrated assessment models (IAMs), specifically, Dynamic Integrated Climate-Economy model (DICE), Policy Analysis of the Greenhouse Effect (PAGE), and Climate Framework for Uncertainty, Negotiation and Distribution (FUND). Data was taken from Nordhaus (2017). One can see that widely different estimates are made depending on the model and discount rate chosen.

What is the ‘correct’ discount rate? This difficult question is not unique to environmental economics; it is pervasive throughout government decision-making. The choice of discount rate, for example, can change public health strategies; for example, see Schad and John (2012). The very long term nature of climate change, however, amplifies the sensitivity of results to discounting. The widely different estimates of the SCC provided by, say, DICE (Nordhaus, 2011) and the Stern Review (Stern, 2007), fundamentally come down to using different discount rates (Hope and Newbery, 2006; Pindyck, 2017). Table 3.1 shows how the 2020 SCC varies across three different models according to the chosen discount rate.

The pure time preference, $\rho$, introduced in Chapter 2, is the most controversial component of the commonly used Ramsey discount rate[44], as it invokes ethical questions about how different generations should or do value one another. Nordhaus (2007), for example, argues that this can be empirically observed. The time preferences indicated by observational studies, however, can vary from 0% to 96000% (Frederick et al., 2002). It is also difficult to unpick exactly what is being measured. Does an observed discount rate reflect solely the pure time preference, or also uncertainty, or forecasts of subsequent income (Frederick, 1999)?

Stern (2007) takes a different approach, and argues from an ethical standpoint that $\rho$ should be minimal, but not zero, so that different generations are given very nearly equal weight. The nonzero $\rho$ acknowledges the infinitesimal risk that future generations may not exist, and so should not be given precisely the same weight as people alive today.

If discounting at Nordhaus' rate, future economic costs would have to be extremely high for it to make economic sense for the current generation to take strong action against climate change. Very low discount rates, however, mean that people alive today would be expected to give their preferences almost the same weight as every other possible future generations'.

We are faced with the dilemma met in Chapter 2: *should* discounting be positive, i.e. describe how things are, and, if so, *can* discounting be positive? Alternatively, should models used to inform government policy instead reflect how things should be? And, if so, what are the appropriate values? Should today's generation shoulder the full costs of preventing climate change? Is discounting a concept that is even valid across generations? Or is it only applicable to a certain individual, group or project as they move through their lifetime? Are different generations incommensurable? Is it appropriate to use the same tools to value one's own future consumption as to value future people's consumption? Surely for many people, these two concepts are very different. And how do we know what future generations' preferences will be?

In short, there is no consensus amongst economists on the discount rate, or indeed on whether discounting is an appropriate framework for intergenerational decision-making, and no resolution is

[44] See Chapter 2 for an explanation of the Ramsey discounting model.

in sight (Gollier, 2013).

#### 3.1.2.2 Equity weights

As described in the previous chapter, many IAMs have introduced equity weighting into their social welfare functions (SWFs). While they are controversial, as many economists are uncomfortable with introducing normative elements into economic analysis, all of the prominent IAMs that focus on estimating the economic consequences of emissions and adaptation policies feature equity weights.

Equity weighting can have a large impact on results. Using a 3% discount rate, Hope (2008) finds that introducing equity weights into PAGE2002 increases the SCC from $58 to $78 per tonne. Hope (2008) puts this relatively small impact down to the emissions scenario explored, in which interregional inequality falls as time goes on, so larger damages fall when income inequality is less severe. Hope (2008) then notes that the inequality aversion coefficient[45], $\eta$, also appears in the discount rate, so it is inconsistent to change equity weights in the welfare function whilst holding the discount rate constant[46]. When adjusting the discount rate accordingly, introducing equity weights is then found to reduce the SCC, as the higher discount rate outweighs the increased damages from equity weighting.

Tol (2002) finds the same result using FUND, unless regions 'cooperate', i.e. unless the sum of all the regions' welfare functions is optimised, instead of each region individually optimising their own welfare function. With cooperation, Tol (2002) finds that the dominating effect depends on the chosen value of $\eta$.

Anthoff and Emmerling (2016) uses RICE-2010, and discovers that for lower values of risk aversion the discounting effect dominates. For an inequality aversion coefficient above approximately 0.6, however, equity weighting dominates and the SCC increases. When using FUND 3.9, Anthoff and Emmerling (2016) observes that equity weights always dominate discounting effects, so increased inequality aversion increases the SCC.

Much like the debate around discounting, many economists are concerned that IAM SCC estimates vary to such a degree as a result of weights that cannot be objectively determined. This explicit influence of values on results does not sit comfortably with positive economists.

[45] As described in Chapter 2, this is the negative consumption elasticity of marginal utility of consumption.
[46] Although one could argue that aversion to inter-regional inequality and aversion to inter-generational inequality are not necessarily equivalent.

#### 3.1.2.3 Commensurability

CBA requires addition, and so can only be performed if all costs and benefits have the same units. This is problematic as, while climate change may cause economic damage, it may also impact on health, ecosystems and aesthetics, none of which are easily expressed in the same units.

CBA economists have, nevertheless, developed various methods to estimate the monetary worth of nature and other market intangibles. These tools include 'hedonic pricing' and 'contingent valuation'. Hedonic pricing ascribes value by, for example, statistically comparing the prices of houses next to a park with the prices of similar houses not near a park, and interpreting the difference to be the value of parkland. Contingent valuation directly asks people how much they would pay to get access to, say, a forest ('willingness to pay' or WTP), or how much compensation they would be prepared to accept for having a forest taken away from them ('willingness to accept compensation' or WTA).

These techniques are frequently criticised. Shortcomings to contingent valuation include:

- The price that people are willing to pay for, say, nature, is unlikely to be independent of what other people are prepared to pay (Sen, 2000). Contingent valuation does not account for this.
- People's real life choices often don't mirror their answers to hypothetical questions (Haab et al., 2013).
- Stated preferences can change depending on how the question is framed (McFadden and Train, 2017).

Similarly, problems with hedonic pricing include:

- Markets are not perfectly efficient; they often misprice goods, as demonstrated by asset bubbles.
- Behavioural economics indicates that people often do not behave like 'rational decision makers' (Gradinaru, 2014). Consumer behaviour, therefore, does not necessarily reveal 'rational' preferences.
- Market prices aggregate desires on a 'one dollar, one vote' basis, i.e. the rich's preferences count for more than the poor's.
- Market prices only reflect the current generation's preferences.

A particular area of contention is the 'value of statistical life' (VSL) (Ackerman, 2008). This estimates how much people are willing to pay to avoid fatality risks, and is used to include changes to mortality rates in CBA. It is determined by statistically assessing wage differences between safe and dangerous jobs. Different studies, however, have produced very different results; for example, Hultkrantz and Svensson (2012).

Hedonic pricing and contingent valuation will also vary depending on the wealth of the people or market being surveyed (Viscusi and Masterman, 2017). To account for this, when comparing individuals or regions with different incomes, should one, as was explored in Chapter 2, introduce equity weights, and, if so, which equity weights are appropriate?

Many economists, moreover, argue that there is an intellectual flaw with trying to put monetary values on non-market goods and services, as this approach hinges on such goods being *equivalent* to a given amount of money; for example, Aldred (2002). They claim that no amount of extra consumption could sufficiently compensate humanity for, say, the loss of a unique eco-system or species. So does it make sense to try to value such things in monetary terms? Similarly, can the value of human life really be captured in dollars and cents and, if not, does it make sense to try to force it into a CBA framework? Money is a medium of exchange; goods and services only have monetary values because they can be traded. Without exchange, money has no use or meaning.

As was seen in Chapter 2, New Welfare Economics claims an ability to rank different policy options 'scientifically', i.e. without making value judgements. Even ignoring the criticisms levied towards this in the previous chapter, this objective ranking is only possible if one has a single criterion, such as economic growth. If additional criteria are introduced, then one must weight them to rank policies. This weighting process is clearly value-laden, and so problematic for many economists. Attempting to convert impacts on health, ecosystems and aesthetics into monetary units is an attempt to collapse a multi-dimensional problem onto one dimension, without explicitly acknowledging the values underpinning the conversion process. Its proponents, nevertheless, argue that CBA makes exploring the merits of different policy decisions objective (Ackerman, 2008).

One-dimensional CBA is one of many possible ways to frame a problem, with an alternative being cost-effectiveness analysis. The latter takes a policy goal set outside of CBA, and then uses CBA to find the most cost-effective way to achieve that objective. A further possibility is multi-criteria analysis, which does not try to force all units onto the same metric. Factors are instead evaluated in their natural units, and policies are assessed against many different metrics.

If one weights the different criterion in a multi-criteria analysis, it is still possible to determine an 'optimal' policy. Weighting different criteria, however, makes value judgements explicit, and one can explore how the ranking of different possible states depends on the weighting of the different criteria. If the weights are highly uncertain, then the concept of an optimal policy becomes dubious. The emphasis instead often shifts towards exploring trade-offs, as goals may conflict with one another. The term ‘sustainable development’, for example, indicates the balancing of two, sometimes contradictory, objectives.

#### 3.1.2.4 Uncertainty

One faces risk when all possible outcomes and their probabilities are known. An example is rolling a dice. Uncertainty, on the other hand, occurs when one’s knowledge of either the outcomes or their probabilities is limited. ‘Quantifying uncertainty’ means estimating how model outcomes may be affected by uncertainties surrounding parameters, structure, observational errors and numerical approximations of solutions. Where observational outcome data is available, regression, Bayesian, Markov chain Monte Carlo (MCMC) and Generalised likelihood uncertainty estimation (GLUE) methods are often deployed. This is known as inverse uncertainty quantification, as the model and associated uncertainties are inferred from the data. Where data is sparse or unavailable, one instead typically uses sensitivity analysis or forward uncertainty propagation, for example, Monte Carlo simulations, to explore uncertainty in model output variables given a specified scenario, i.e. set of values for model input variables. A good overview of inverse and forward uncertainty quantification methods can be found in (Beven, 2009).

‘Deep uncertainty’, sometimes called ‘Knightian uncertainty’, occurs when quantifiable information is so sparse that the PDF associated with an uncertainty cannot be ascertained. An example is the Intergovernmental Panel on Climate Change’s (IPCC’s) Representative Concentration Pathways[47] (RCPs) (IPCC, 2014). These GHG atmospheric concentration scenarios do not have associated probabilities, as there is insufficient information to estimate the relative likelihood of the socioeconomic assumptions underpinning these scenarios. Deep uncertainty is a problem for methods such as CBA that rely on calculating expected values, and so require PDFs or exact knowledge.

Our understanding of climate change is highly uncertain, both from an environmental and economic perspective, and much effort has been made to quantify uncertainty. Sources of environmental uncertainty include the response of GMST to changes in atmospheric $CO_2$ concentration. This ‘climate sensitivity’ involves complex feedback loops that scientists struggle to predict (Bony et al., 2006). Attempts to estimate this sensitivity have used a variety of tools, including model simulations, instrumental records of GHG atmospheric concentrations and temperature, and paleo records.

[47] See Section 3.2.3 for a description of the Representative Concentration Pathways (RCPs).

Another source of climate-related uncertainty is the ocean circulation response (Barnes and Screen, 2015); but many other examples exist.

On the socioeconomic side of IAMs, economic and demographic projections are uncertain, particularly given the time-scale over which climate change damages are likely to occur. IAM 'damage functions', which estimate the annual cost or benefit to an economy or sectors within it arising from changes in annual mean temperatures, are highly speculative. While they theoretically draw upon a range of external impact studies, the latter are often exploratory rather than confident estimates. Moreover, there are very few impact studies that estimate the economic consequences of a GMST increase greater than 3°C. In the studies surveyed in the IPCC's fifth assessment report (IPCC, 2014), for example, 19 studies explore damages for a 1°C to 3.5°C change in GMST, while only one study explores a higher temperature change[48] (Journal of Economic Perspectives, 2015). Nordhaus and Sztorc (2013) similarly observe that "estimates of damage functions are virtually non-existent for temperature increases above 3°C". IAMs, however, often look at scenarios where GMST increases by as much as 6°C. So how do IAMs estimate damages at such levels?

Approaches include performing regression analysis over the range in which damage estimates are available and then extrapolating the established relationship to higher temperatures, or using expert guesses of functional forms that can then be calibrated based on one or two damage estimates from lower temperature changes. Expert guesses are also sometimes used for lower temperature changes, where impact estimates are not available, or where it's believed existing impact estimates need to be adjusted to reflect omitted factors. Prieg and Yumashev (forthcoming) provides a summary and critique of the traditional methods deployed.

A recent wave of impact studies has used econometrics to estimate the relationship between temperature and total economic growth across a large number of countries. Burke et al. (2015), for example, uses regression analysis on data from 166 countries between 1960 and 2010 to estimate the effect of temperature on growth in real gross domestic product (GDP) per capita, specifically whether deviations from growth trends appear to be driven by deviations from temperature trends. Individual response functions are generated for the different countries and then combined to form a global response function. Taking only the first or the last 20 years of the time period generates essentially the same results, which suggests that technological advancements and increased wealth have not altered the relationship. While year-on-year fluctuations in temperature in any given country cover only moderate increases in temperature, the wide range of countries studied have very different average temperatures, so, by placing all the countries on the same curve, the effects

[48] This study explores a 5.5°C increase in GMST.

of a wide range of temperature increases are estimated.

Such studies provide a more compelling calibration approach then the methods usually deployed. To date, however, PAGE-ICE (Yumashev et al., 2019) is the only IAM to have based its damage function on such results; but other IAMs are likely to eventually follow suit. Econometric analysis, however, will not resolve all IAM uncertainties. The Burke et al. (2015) approach, for example, assumes that all countries can be placed on the same curve. In reality, economies and the environment may struggle to adapt to large increases in average temperature levels that occur over a relatively short time-scale or high volatility. The Burke et al. (2015) analysis also tells us nothing about what will happen if countries at the top end of the average temperature spectrum experience a large increase in temperature, and unfortunately these countries tend to be among the poorest. IAMs additionally typically assume that all damages are repaired by the next time-step, which may be overly optimistic, particularly as resources will need to be diverted from other activities towards repairing climate damages. In other words, there may be growth rate, rather than, or in addition to, level effects. Moreover, while econometrics may work for a total economic damage function, there may be insufficient sector-level data for a wide variety of countries to establish sector-level damage functions in this manner[49]. Depending on the research question being addressed, a sector-level approach may be required; for example, if one hopes to estimate the extent that different sectors are vulnerable to climate change. Finally, econometric analysis cannot resolve climate response uncertainties. Nevertheless, such studies provide a way forward for IAMs to improve upon some of the current problems with damage functions.

As discussed, IAMs in the first category are large and complex, which means they are typically deterministic. To explore uncertainty, different models produced by different modelling teams are often used to generate climate and biophysical results for the same scenario. Probabilities are not assigned to the results for different scenarios; the latter are merely used to get an idea of the range of outcomes that may occur. For example, this is the approach taken by the IPCC in its Assessment Reports. IAMs in the second category, meanwhile, are smaller and simpler, and so the effect of uncertainty on a model's output can be explored. While they typically use the non-probabilistic GHG and socioeconomic scenarios generated by IAMs in the first category as exogenous inputs, for each of these scenarios they attempt to quantify the uncertainty around their output variable, which is usually the SCC. FUND and PAGE, for example, use expert guesses or the range of estimates provided by external studies to suggest PDFs for over 100 uncertain variables, be they a scaling factor for the

[49] Although there are many existing econometric studies exploring the relationship between temperature and labour productivity or agricultural output.

climate impact at a calibration temperature or polynomial degree which determines the convexity of the damage function. Monte Carlo simulations[50] are then performed to estimate a PDF for the SCC. However, not all IAMs in this category are highly stochastic. Some, such as DICE, are deterministic or present only a very simple sensitivity analysis. To explore structural uncertainty, for example, Nordhaus (2017) varies three variables in DICE 2016R: the damage parameter, productivity growth and equilibrium temperature sensitivity. As with IAMs in the first category, research using IAMs in the second category also frequently compares results generated by the different models.

As explored in Prieg and Yumashev (forthcoming), the choice of methods used to derive economic damage functions and their associated PDFs is often not explained in the model technical documentation and is sometimes puzzling. Moreover, the studies providing the data used for calibration are often very out-of-date; for example, they are frequently from the 1990s. This reduces the data points available for calibration and so also limits the calibration methods that can be applied. In addition, scientific progress has been made over the past twenty years that will not be incorporated. Many IAM PDFs are based on guesswork, not modelling or observation. In FUND 3.9 (Anthoff and Tol, 2014a), for example, agricultural damages due to the rate of change of temperature are assumed to be proportional to rate of change in GMST raised to a power. The PDF of this uncertain power is transparently stated to be an expert guess that is not derived from any damage studies. Similarly, the PDFs in PAGE are simply assumed to be triangular. PDFs underlying catastrophic climate events and their impacts are particularly spurious. The likely consequent damages are essentially unknown, and the tails of these distributions might be fatter, which could have a large impact on the resulting CBA (Weitzman, 2014, 2009). In short, the uncertainty surrounding the economic consequences of climate change is, at least currently, deep.

With the exception of catastrophic climate events, the PDFs underpinning climate uncertainties are better understood than their economic counterparts. As described in Chapter 1, research into the environmental side of climate change naturally began before economists started thinking about the subsequent economic consequences. It is, thus, not surprising that our understanding of climate uncertainties is more developed. Yet there is nevertheless much work to be done to confidently understand even key climate uncertainties, such as the climate sensitivity (Freeman et al., 2015). As discussed, there is also currently a lack of input data to define many of the thousands of parameters that form large climate models.

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[50] Monte Carlo simulations run a model thousands of times using random sampling of any uncertain variables from a specified PDF. Through thousands of simulations, one can thus build up a probability distribution for the model’s outcome value. Monte Carlo analysis also allows one to see which uncertain variables have the largest impact on results (sensitivity analysis).

#### 3.1.2.5 Summary of key criticisms

This chapter does not aim to provide a comprehensive list of critiques of IAMs, but rather to give a flavour for key areas of concern – discounting, equity weighting, commensurability and uncertainty. All these shortcomings have left IAMs open to extensive criticism. Pindyck (2013), for example, writes

*"These models have crucial flaws that make them close to useless as tools for policy analysis: certain inputs (e.g., the discount rate) are arbitrary, but have huge effects on the SCC estimates the models produce; the models' descriptions of the impact of climate change are completely ad hoc, with no theoretical or empirical foundation; and the models can tell us nothing about the most important driver of the SCC, the possibility of a catastrophic climate outcome. IAM-based analyses of climate policy create a perception of knowledge and precision, but that perception is illusory and misleading."*

Risbey et al. (1996) similarly argued that it is difficult even to use IAMs heuristically to make, say, order of magnitude estimates or to explore temporal sequencing, as even qualitative conclusions will be heavily influenced by the flawed assumptions underpinning the models.

If this analysis is correct, then there is serious cause for concern, as IAM results are frequently referenced by the IPCC and government environment departments, and appear to have influenced public policy (Schwanitz, 2013).

#### 3.1.2.6 Can IAMs be tested?

In an ideal world, one would divide a data set in two, and use half of the data to calibrate an IAM, and half to verify it. Could IAM predictions from twenty years ago, for example, be tested against climate change damages suffered over the past, say, ten years? How would one identify and measure what the losses from climate change have been? This would require knowing how sectors and economies would have performed in the absence of climate change, with everything else staying the same. One cannot observe such macroeconomic counterfactuals. Damages from climate change in the recent past and near future are also likely to be small (Nordhaus, 2007), and so even more difficult to distinguish from other factors affecting economic performance.

The inability to test macroeconomic counterfactuals is a problem for validating many types of models, not just IAMs. Many disciplinary macroeconomic models, for example, similarly cannot really be tested predictively. This includes axiomatic computable general equilibrium (CGE) models, which are generally not used for forecasting, but instead for estimating what the impact of an isolated policy would be, assuming no other developments in the economy. As with IAMs, one cannot test the accuracy of such ceteris paribus estimates, as this would require knowledge of a counterfactual world for which one has no observational evidence. While statistical techniques attempt to unpick causal effects, as will be shown in the subsequent section of this chapter, there are many challenges associated with statistically testing complex nonlinear systems.

Given the lack of counterfactual data, there is no consensus on how to evaluate IAMs (Schwanitz, 2013). Some emphasise transparency, particularly with regards to assumptions, so that individual components of the models can be evaluated, even if predictions from the entire system cannot (Rotmans and Van Asselt, 1996; Schwanitz, 2013). Even if this approach is taken, however, one must remember that economies and the climate are complex, dynamic non-linear systems, so one must approach IAM estimates with caution, particularly when they are generated for long time frames.

### 3.1.3 Modelling complex nonlinear systems

If $A + B$ is fed into a linear system, the output generated is the same as if $A$ and $B$ had been fed into the system individually, with their outputs then summed. In nonlinear systems, this principle is broken. Meanwhile, a dynamical system is one containing variables that are time dependent.

Most nonlinear differential equations are not integrable. Such systems do not have closed-form solutions, and one must instead use numerical methods to see how they evolve. Nonlinear systems can have predictable steady states or periodic behaviour, but they can also exhibit quasi-periodicity or complex behaviours that are extremely difficult to predict. In addition, small inputs can translate into large outputs. This can result in small measurement errors for initial conditions translating into large differences in long-term prediction trajectories. Small uncertainties can thus be amplified over time, so rendering predictions useless (Kleeman, 2011). Such systems may also have multiple equilibria or 'attractors', where the latter is an area of the map of possible outcomes towards which a nonlinear dynamic system eventually evolves and orbits, periodically or otherwise. This means that a small deviation has the potential to suddenly shift the system into a new regime (Lorenz, 1963).

Complex systems, such as the atmosphere or an economy, have many different parts that interact. While the isolated individual components of such systems may be predictable, interactions and feedback effects can make the system unpredictable. An example of this is the double pendulum, a non-integrable system. While the dynamics of each individual pendulum, in isolation, are easy to predict, when the pendulums are connected the behaviour becomes chaotic (Shinbrot et al., 1992). To precisely predict such systems, one would need to have perfect knowledge of all the forces acting on every component, along with perfect measurement of starting conditions for each component, and extensive computing power. Without these capabilities, the system may exhibit behaviour that cannot be predicted from studies of isolated components – a phenomenon called 'emergence'. The double pendulum has only two components, and already exhibits complexity. The atmosphere or an economy contains countless parts, so the level of knowledge, measurement and computer power required to precisely predict such systems is high indeed. Furthermore, while the forces and dynamics around single pendulums are well known, with naturally occurring complex systems it can be difficult to isolate components and determine the equations governing them. Trying to infer such information from emergent behaviour is extremely difficult (Wang et al., 2011).

The study of nonlinear dynamics is in its infancy, with mathematical tools still being developed (De Gooijer and Hyndman, 2006; Vlad et al., 2010). This is reflected in the performance of such models versus linear ones; namely, nonlinear models often don't produce better forecasts (Clements et al., 2004; De Gooijer and Hyndman, 2006). Understanding the behaviour of complex systems is considered to be one of the key challenges in modern science (Cheng et al., 2015).

While statistics can often be useful for exploring microdynamics, time-series analysis, for example, struggles to deal with interacting processes and non-stationary behaviour, where means and variances evolve with time (Cheng et al., 2015). Such behaviour is common in complex, dynamic non-linear systems (Cheng et al., 2015). While techniques that can deal with non-stationary processes, such as multi-layer perceptron (MLP) and generalised autoregressive conditional heteroscedasticity (GARCH), have been developed (Golestani and Gras, 2014), such methods typically can only cope with certain types of non-stationary behaviour (Cheng et al., 2015). Non-stationary time series analysis thus still poses great challenges. Furthermore, the data demands required to overcome such difficulties are high, as models of complex systems commonly have many variables relative to data points, which reduces statistical power.

The problems of non-stationarity have been known for many years. Robert Solow, for example, argued that it is "straining credulity" to believe that economic processes are stationary:

> *"As soon as time-series get long enough to offer hope of discriminating among complex hypotheses, the likelihood that they remain stationary dwindles away, and the noise level gets correspondingly high. Under these circumstances, a little cleverness and persistence can get you almost any result you want. I think that is why so few econometricians have ever been forced by the facts to abandon a firmly held belief."* (Solow, 1985).

Macroeconomic models' current forecasting abilities, even for the near-future, reflect these challenges. Researchers at the Federal Reserve, for example, examined US GDP growth and inflation forecasts for between 1992 and 2004 and found that dynamic stochastic general equilibrium (DSGE) models appear to forecast "very poorly", although outperform econometric models and expert guesses (Edge and Gurkaynak, 2011). DSGE predictions of inflation for even one quarter ahead had an $R^2$ of only[51] 0.13. For quarters further out, the $R^2$ fell to nearly zero. Fildes and Stekler (2002) surveyed the literature evaluating UK and US real GDP and inflation forecasts, and found that forecasts outperformed those generated by naïve random walk models, but not significantly so. Fildes and Stekler (2002) also found only mixed evidence for macroeconomic forecasts improving over the latter decades of the twentieth century as econometric techniques improved. Meanwhile, in May 2007 and 2008, in the midst of the financial crisis, the OECD predicted GDP growth for the following year in 40 different countries. These estimates were ultimately wrong by an average of 2.6 percentage points – a very large error for GDP growth (Richardson et al., 2014).

To add value, researchers must therefore remember that IAMs deal with nonlinear systems and imperfect models, knowledge, and measurements, so, given the tools currently available, one cannot make precise predictions, even for the next decade, let alone over the climate change timescale. This is a big conceptual leap for the economics profession which, since Milton Friedman's influential essay (Friedman, 1953), has generally focused on predictive power when evaluating models. Friedman argued that

> *"Truly important and significant hypotheses will be found to have "assumptions" that are wildly inaccurate descriptive representations of reality, and, in general, the more significant the theory, the more unrealistic the assumptions"* (Friedman, 1953)

He goes on to claim that the appropriateness of assumptions is determined not by how realistic they are, but by how well the model, as a whole, makes predictions. As models cannot include everything, they are inherently unrealistic. In fact, successful models will be the most unrealistic, he asserts, as they should have distilled a phenomenon down to its core drivers and eliminated more minor interactions. Friedman's arguments have had an enormous influence on the economics profession and its interpretation of the scientific method (Mäki, 2009).

Moving away from this makes it more difficult to assess a model. Can an imperfect model still have academic value? And, if so, how can we tell which models are helpful, and which are useless or even misleading? To approach this, let us consider what models are for.

[51] $R^2$ is a proportional measure of the extent that realised data can be explained by the model. It varies from 0 to 1, where the former indicates that none of the data can be explained by the model and the latter means that the model can explain all the data.

### 3.1.4 Why do we build models?

Models do not perfectly reflect reality. The latter is too complex for mankind to encapsulate in a series of rules. Even if such a model could, in theory, be created, there is insufficient computing power to run it. So models are instead simplified abstractions of reality that help us explore questions and discover new ones; they are tools to help us learn. While Friedman argued that the purpose of an economic model is to make predictions, many natural scientists, social scientists and philosophers take a different view.

Solow, for example, advised economists to use models to organise thoughts, discover unexpected links, develop plausible causal narratives, and to make “rough quantitative judgements” (Solow, 1985). Another perspective is that models are an effective way to explore the implications of a theory, to differentiate between theories, and to compare and contrast them. When different models are used to simulate the consequences of the same set of assumptions, examining the differences between the results produced can help illustrate how modelling frameworks influence the projected outcome. In addition to exploring theories, models can be used to probe how different processes may influence and interact with one another (Bharwani et al., 2005). Agent-based models (ABMs), for example, can help explore the emergent behaviour of interacting processes and complex systems. They can also be used to generate scenarios to explore a range of possible outcomes and to see if counterintuitive outcomes could occur. Similarly they can help one better understand policy questions and problems (Morgan, 2017). Explicitly speculative models and theories have even been put forward with the stated aim of prompting discussion and highlighting areas about which there is a paucity of knowledge. The Kuznets curve, which suggests a relationship between economic development and economic inequality, is an example of this (Kuznets, 1955). By highlighting areas where our understanding is deficient, models can thus help direct further research and data gathering (Oreskes et al., 1994).

In the face of deep uncertainty, some argue that expert guesses are good alternatives to formal modelling. Thinking qualitatively, however, can be vague and open to inconsistencies. Expert guesses are filled with just as many assumptions as formal models, only they are less transparently stated; in fact, they probably won’t be declared at all. Expert guesses may also suffer from cognitive biases of which the expert is unaware (Goodwin and Wright, 2010). Building a model forces one to state all assumptions, to think through them as a collective package, and to identify and eliminate logical contradictions in one’s theory.

Climate change is arguably the biggest challenge of our generation. Its estimated effects range from negligible to the complete collapse of ecosystems. Some even argue that global warming may bring benefits. These varying consequences demand different responses from individuals, firms, non-governmental organisations (NGOs) and governments. Fossil fuels, for example, have historically been one of the biggest drivers of economic development (Asafu-Adjaye et al., 2016). In this light, is it preferable to curb carbon emissions and potentially reduce economic growth? If so, what are the pros and cons of the different ways to do this, and, if future generations are likely to be wealthier than people today, won't they be better placed to cut consumption? These are the questions that IAMs and impact studies address; it would be absurd and irresponsible for academics to not consider these issues. Macroeconomics, similarly, should not disappear despite the profession's frequent failure to make successful predictions.

So the question is not 'should one model the impacts of climate change', but rather 'at what point do these models become misleading rather than helpful?' The answer is when results are oversold. Even Robert Pindyck, perhaps the most vocal critic of IAMs of the second kind, acknowledges that the problem is not people trying to model uncertain interactions between the economy and GHG emissions, but rather that results are sometimes communicated with the same degree of confidence one would expect from a scientific experiment or randomised controlled medical trial (Pindyck, 2017). He calls this "the veneer of scientific legitimacy", and takes particular issue with precise quantitative conclusions, such as calculating the SCC, or prescribing an *optimal* greenhouse gas mitigation strategy (Pindyck, 2017).

IAMs thus can have many purposes, even if they can't confidently be used to make precise, verifiable predictions. They can help identify key relationships between the climate and economies, help us better understand current theories surrounding growth and climate change, eliminate logical contradictions, help organise thoughts, force one to identify and understand assumptions, highlight areas where understanding is deficient, encourage debate and future research, and provide a logical and consistent framework for developing scenarios. The questions one asks and how results generated by IAMs are viewed, however, should differ to approaches taken when dealing with models with high predictive power.

This thesis uses IAMs and damage studies in this light. Precise estimates and confidence intervals for the effect of climate change on income inequality in various countries will not be attempted; nor will any 'laws' be formulated. The focus is on exploring tendencies and the factors driving them, seeing if any persuasive patterns emerge, and putting forward qualitative propositions.

## 3.2 Modelling under uncertainty

### 3.2.1 Frameworks for dealing with climate and economic uncertainties in IAMs

While the PDFs used and generated by the second category of IAMs are likely to be highly flawed, they are, however, still useful and interesting. They are an attempt to explore the propagation of uncertainty, can indicate which uncertainties may have the greatest impact on results and so help prioritise future research, and have prompted academic debate[52]. Academics should continue trying to improve the quantification of climate and economic uncertainties and understand their propagation, while making it very clear that the degree of confidence in many of the model's PDFs is currently low, and so, given the current deep uncertainty, the output PDF is only exploratory.

The preceding analysis, however, casts doubt on the ability to use CBA to recommend, for example, cost-optimal emissions trajectories. Instead non-probabilistic decision frameworks that were specifically developed for dealing with deep uncertainty will often be more appropriate.

Non-probabilistic methods generally consider how robust decisions are to assumptions about the future being wrong. Robustness is defined to be how well a decision, such as investment to facilitate adaptation to climate change, performs across many different non-probabilistic scenarios, say, the different future climates that may result. Performance can be evaluated, for example, using scenarios of the different costs and benefits that could emerge from each climate scenario, and netting these against the cost of the adaptation investment. This result could then be compared to a specified threshold for strategy failure. The policy that is most robust to different possible futures might not be the 'optimal' policy in any given future. Model users are, thus, forced to entertain the idea that decisions may involve trade-offs, for example, between maximising growth in one possible future, versus making decisions that perform satisfactorily across many different futures. The goal is generally not to definitively rank policies, but to inform policy makers about uncertainties, vulnerabilities, and trade-offs. Rather than policy makers being given the impression that there is an objectively 'best' policy, these methods encourage the decision maker to consider their priorities. For example, what is the maximum cost the decision maker is prepared to potentially endure? What gains would the decision maker be happy to sacrifice to avoid potentially triggering this cost threshold? The recommended decision may thus differ for different decision makers in line with their values and goals. For example, when probability distributions are unknown, some argue that a maximin approach should be followed, where the focus is on optimising the worst case scenario. Homeowners buying home insurance and large US defence spending during the Cold War are

[52] For example, see Weitzman (2009).

examples of this ‘precautionary principle’ in action (Woodward and Bishop, 1997).

Scenario analysis is a common starting point for exploring highly uncertain futures. Scenarios must be plausible and internally consistent, although many may be deemed unlikely. With a mind to the questions being addressed, uncertainties that could have a large effect on outcomes are identified via a literature review or through discussions with stakeholders, and used to inform the choice of scenarios. A different “axis of analysis” spanning each key uncertainty is often created (Laurent et al., 2015). One should then attempt to select scenarios so that the ranges of these axes are well explored. Scenarios are typically not ascribed a probability, so unlikely but disastrous events are given the same consideration as seemingly probable, but more minor outcomes. Note that there is no claim, however, that the full range of possible outcomes has been represented. One is exploring uncertainties, without attempting to quantify them.

These ensembles of scenarios are then used to stress test decisions, identify weaknesses, explore key drivers and relationships, make precautionary investments, and develop contingency plans. The emphasis is not to identify a ‘best’ solution, but instead to encourage decision makers to understand and explore different trade-offs. What are the objectives? What trade-offs are tolerable? Do any decisions perform acceptably in all possible worlds? What decisions leave one locked-in and unable to manoeuvre should the future not turn out as expected? By considering their values, decision makers should come to their own idea about the most appropriate choice; this should not be decided by the model or modeller, who exists merely to present alternatives and their pros and cons.

As discussed in this chapter, scenario analysis is already a popular tool for exploring climate change, since the IPCC uses different IAMs in the first category to generate a range of future population, economies, technology and GHG emissions scenarios, which are not assigned probabilities. IAMs in the second category also typically use these scenarios as non-probabilistic exogenous inputs, before attempting to quantify the uncertainty around their output variable in each of these scenarios. Scenario analysis is also frequently used in other disciplines. The Bank of England, for example, used scenarios to explore the possible impacts of Brexit (BoE, 2018). In addition, businesses sometimes use scenario analysis to aid decision making under deep uncertainty, as do defence ministries and armed forces (Bradfield et al., 2005; Brown, 1968).

Scenario analysis is sometimes used in combination with formal decision-making techniques. Robust decision making (RDM), for example, explores which decisions perform well in a variety of plausible future scenarios, and highlights trade-offs between satisfactory outcomes in a wide variety of futures and optimal performance (Lempert et al., 2003)[53]. A decision is proposed, and then a large number of scenarios in which the decision succeeds or fails as per specified terms are then collected. Statistical techniques are then often used to identify which uncertainties or assumptions seem key to success or failure. RDM has been used in a variety of environmental economic decision contexts, including resource management, and capital investment (Kalra et al., 2014).

Non-scenario, non-probabilistic frameworks for decision making under deep uncertainty have also been developed. Info-gap theory, for example, starts with a 'best-guess' of parameters and model structure, and then explores how wrong one would have to be in one's assumptions for a given decision to not meet a given target. Decisions that can withstand the greatest error in uncertain parameters or structure are then highlighted. Where multiple parameters are uncertain, they can be assigned weights to indicate if some are more uncertain than others, or can all given equal weight if they are all equally uncertain. The methodology is frequently used in ecological modelling to help determine, say, conservation strategies (Hayes et al., 2013), or to help tackle environmental problems, such as, flood risk (Hine and Hall, 2010). The initial 'best guess' for a parameter or the model structure, however, affects info-gap results.

### 3.2.2 Choice of scenario analysis

Due to the deep uncertainties present, a non-probabilistic approach was favoured in this thesis. RDM, info-gap theory, maximax and maximin analysis are all focused on assessing strategies. The goal of this project was not to rank policies, but rather to explore mechanisms, tendencies, resilience and vulnerabilities. As such, scenario analysis was deemed the most appropriate methodology.

Two axes of analysis for scenarios were identified. The first was uncertainty surrounding the extent of climate change damages. Here, IAMs and impact studies were used to generate a range of climate impact scenarios across this axis.

The second axis of analysis was uncertainty around the structure of economies when damages occur. IAMs estimate damages in a series of time-steps, for example, 2020, 2030, etc, so ideally one would have a social accounting matrix (SAM)[54] for each selected country at the start of each time period. As described in Chapter 4, a SAM is a map of monetary flows between different sectors, institutions, and household groups in an economy over a given time period, usually a year. The idea that a detailed map of a nonlinear system could be projected far into the future is absurd. To explore uncertainty around future economic structures, scenarios were instead run using SAMs for a wide

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[53] Sometimes probabilities are ascribed to different scenarios; see Hall et al. (2012) for an example.
[54] The methodological choice to use input-output analysis (IOA) on Social Accounting Matrices (SAMs) is explained in Section 3.3.

range of existing economies, with many different drivers of growth, and starting levels of income and inequality[55]. This helped explore how climate change induced income inequality may vary according to the structure of underlying economies. Moreover, while significant climate change damages are not generally anticipated until the end of the twenty-first century, there is much uncertainty underlying this prediction. As seen in Chapter 2, studies such as Rozenberg and Hallegatte (2015) suggest that sizable effects could emerge as early as 2030, and economic structures today are likely to share similarities with economies over the next decade. This is explored in more detail in Chapter 5.

### 3.2.3 IPCC scenarios

This thesis' case studies use the Special Report on Emissions Scenarios (SRES) and the Representative Concentration Pathways (RCPs), which were compiled at the request of the IPCC, and so are the most commonly used scenarios in the climate change literature. Thanks to the IPCC, the research community is generally familiar with the scenarios, which expedites modellers' understanding of one another's work, and allows results from different studies to be compared. The available data also enables researchers without expertise in the socioeconomic, technological or emissions modelling used to generate the scenarios to explore consequences on, say, ecosystems or economies. Moreover, to save time, even researchers with the aforementioned skills can use the scenarios as a starting point for further analysis.

The SRES are 40 scenarios that explore different plausible future emissions pathways from 1990 to 2100 for various GHGs. They stem from assumptions about the factors driving emissions, such as the extent that societies prioritise the environment, the rate of economic growth, the degree of globalisation, technological developments, and changing demographics. They are split into four families, A1, A2, B1, and B2, with each family sharing characteristics yet containing different scenarios produced by different IAMs. The A1 family contains three sub-families, A1F1, A1T and A1B, which reflect three different fuel-type storylines, respectively, predominantly fossil fuels, predominantly zero-carbon sources, and a balance of both types. A summary of the key characteristics of each SRES family can be found in Appendix A. Six different models were used across the 40 scenarios. For the full description of the scenarios, see (IPCC, 2000).

While the SRES assume different societal attitudes towards environmentalism, they do not contain any climate change policy interventions and so cannot be used to explore possible mitigation efforts. In addition, as various socioeconomic assumptions drive each scenario, one cannot change, say,

[55] The literature review in Chapter 2 suggested that starting levels of inequality and GDP may influence the extent that climate change affects inequality.

assumptions about energy intensity, without having to generate a new emissions scenario. This is why there are so many SRES. The sequential approach also makes it difficult to explore socioeconomic drivers and climatic effects separately.

To address these shortcomings, a new set of benchmark scenarios, the RCPs, were later developed by the climate modelling and IAM communities at the request of the IPCC. There are four scenarios, called RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5, which reflect possible low, intermediate, intermediate, and high concentration trajectories respectively for various GHGs. The numerical labels correspond to the likely radiative forcing[56] in 2100, measured in watts per square meter, arising from the given GHG concentration pathways. As the starting points for the RCPs are radiative forcing projections, the socioeconomic conditions that give rise to the pathway and the changes to climatic systems associated with the pathway can be studied independently. They thus enable a parallel rather than sequential approach, which saves time[57] and resources, and is easier logistically. One can change a socioeconomic assumption without then needing to generate a new climate scenario. For more information on the RCPs, see van Vuuren et al. (2011a).

In parallel with the development of the RCPs, the IAM community developed Shared Socioeconomic Pathways (SSPs), to explore how the four RCPs might arise. Five qualitative narratives were developed, which covered different development, global cooperation and inter-country inequality trajectories, and these formed the basis of each SSP. Population, urbanisation and GDP projections were then estimated for each SSP. Finally, six different IAMs were used to interpret each pathway, resulting in a range of energy demand, land use change, and GHG and pollutant emissions projection scenarios within each SSP. The key differences between the pathways are summarised in Appendix B. The characteristics of each SSP collectively produce low to high challenges to adaptation and mitigation, as shown in Appendix C. See Riahi et al. (2017) for a more detailed summary of the SSPs.

As different socioeconomic scenarios could give rise to each RCP, there is no unique matching between SSPs and RCPs (Riahi et al., 2017); although only SSP5 produces radiative forcing high enough for RCP 8.5. RCPs 4.5 and 6.0 could arise from any of the SSPs, while RCP 2.6 can be associated with SSPs 1, 2 and 4. RCP 8.5 combined with SSP5 approximately corresponds to SRES A1F1, while RCP 6.5 combined with SSP2 and RCP 4.5 combined with SSP1 approximately correspond to SRES B2 or A1B, and B1 respectively (van Vuuren and Carter, 2014). RCP 2.6 has no clear SRES comparison.

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[56] Radiative forcing is the difference between energy absorbed and energy radiated by the Earth. A positive (negative) imbalance causes the Earth's temperature to rise (fall).
[57] The models can take months to run on supercomputers.

## 3.3 Modelling inequality effects

### 3.3.1 Different macroeconomic models

We need a methodology to extend IAMs and impact studies so that they can estimate the impact of climate change on income inequality, and thus address the research questions outlined in Chapter 2. As such, let us briefly review the main tools currently used for macroeconomic modelling.

#### 3.3.1.1 Input-output analysis (IOA)

IOA solves a set of linear simultaneous equations based upon a disaggregated map of monetary flows in an economy, either an input-output table (IOT) or a SAM[58]. It is a general equilibrium[59] model that assumes that the IOT or SAM is the initial equilibrium state, and then uses linear algebra to model the new equilibrium state after a given exogenous change. The model is typically highly disaggregated, as it is geared towards exploring interconnections between different parts of an economy. Due to its linearity, it is a simple model with restrictive assumptions, which generally makes it less popular with academics. Its simplicity does, however, lend itself to identifying direct versus indirect effects. It is, thus, frequently used to address questions involving economic interdependence; particularly when it is important to understand the mechanisms driving indirect effects, such as when conducting disaster impact analysis, studying resilience, exploring the carbon and water footprints of commodities, or estimating the impact of proposed emissions reduction targets on an economy.

#### 3.3.1.2 Computable general equilibrium (CGE) models

A CGE model is a set of nonlinear simultaneous equations that draw on economic theory to describe an economy. Computer programming is used to iterate parameter values until the model is consistent with a calibration SAM. This SAM is taken to be the initial equilibrium state. An exogenous change is then simulated, and elasticities[60] in the model inform how the economy reacts. Computer programming estimates the new equilibrium state by maximising utility for consumers and profits for producers, while fulfilling given constraints. CGE models are highly popular with policy-focused institutions, such as the World Bank (Grabner, 2014).

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[58] IOTs and SAMs are described in Chapter 4.

[59] General equilibrium occurs when intersecting supply and demand set prices such that all markets clear, i.e. there is no unmet supply or demand.

[60] Elasticities estimate the responsiveness of demand or supply of a good or factor to changes in that good or factor's price, other prices in the economy, and income levels.

#### 3.3.1.3 Dynamic stochastic general equilibrium (DSGE) models

DSGE models are based upon behavioural equations for various economic actors, such as households and firms. They are thus bottom-up models with microeconomic foundations, which, in theory, means they should be able to produce a reliable picture of an economy even if the policy environment changes. This, coupled with their relatively good predictive power, makes them extremely popular with academics (Grabner, 2014). After an exogenous change, programming is once again used to find the new equilibrium state, and, like CGE models, DSGE models assume utility and profit maximisation. Unlike CGE (and IOA) models, they also show the transition between equilibria. They are, thus, dynamic models, as they explore the evolution of variables over time. They are also stochastic[61], as variables are affected by random shocks that cause their values to fluctuate.

#### 3.3.1.4 Agent-based models (ABMs)

ABMs specify behavioural algorithms for agents, where decisions are often assigned a probability distribution. They are typically calibrated against survey data, interviews, experiments, or econometrically estimated preferences. Monte Carlo simulations can then be run to provide a computer simulation of the evolution of a complex adaptive system. Some models also introduce interdependencies between agents. When running the model, equilibrium could emerge, but there is no assumption that it will. ABMs were built to explore the emergent behaviour of systems of multiple, often heterogeneous, agents, and so are frequently used to model social networks, including economies. In ecological economics, for example, ABMs have been used to model land markets, emissions trading, and land use decision-making (Heckbert et al., 2010).

#### 3.3.1.5 Vector autoregression (VAR)

VAR models are econometric, and so use statistics to analyse economic data, specifically time-series. One regresses the current values of variables on their previous values, and sometimes also contemporaneous values of other variables (Rudebusch, 1998). Residuals are then interpreted as exogenous shocks. VAR models are used for forecasting, and do not attempt to explore the mechanisms driving results, while structural VAR (SVAR) models combine VAR with economic theory in an attempt to identify causal relationships.

[61] Stochastic models contain random elements, and so will generate different results from different runs of the model that start from the same given point.

### 3.3.2 Comparing the macroeconomic models

To help decide which modelling approach is most appropriate to answer the research questions outlined in Chapter 2, let us first compare key characteristics across the different models.

#### 3.3.2.1 Level of disaggregation

IOA and CGE models specialise in exploring how different parts of an economy interact with one another and how indirect effects are transmitted across an economy. As such, these deterministic models[62] are typically disaggregated into many economic sectors. In contrast, as DSGE models are stochastic, they are harder to solve, and so these models are generally highly aggregated to expedite programming. The Bank of England's DSGE model, for example, has only five actors, households, enterprises, the central bank, the government, and the rest of the world (ROW) (Nachane, 2016). Multi-sector DSGE models do, however, exist, for example, Rees et al. (2016), but they are far less common. Similarly, different types of firms can feature in ABMs, such as in Caiani et al. (2019), but this is relatively unusual, as ABMs typically focus on heterogenous households rather than heterogenous firms. Finally, while this is unusual, one can include many different economic sectors in a VAR model provided one has a sufficient time-series for each sector; for example, Partridge and Rickman (1998).

ABMs are often designed specifically to incorporate heterogeneity between agents, and to explore the subsequent consequences. IOA models also frequently involve many agents who represent the aggregates of various household groups, such as income deciles, rural and urban households, households with different levels of educational attainment, or different ethnicities. Many CGE and DSGE models, however, have only one representative household. Herault (2007), Mohammed (2018), Verikios and Zhang (2016) and Wang et al. (2017), for example, needed to couple CGE models up with microsimulation models to study the inequality effects of macroeconomic policy. CGE and DSGE models with disaggregated household groups do exist for a few economies, for example, Mahadevan et al. (2017) for Indonesia, Maisonnave et al. (2016) for South Africa, Mythili (2015) for India, Hoagland et al. (2015) for Rhode Island and Massachusetts, and Pouliakas et al. (2014) for the European regions of Archanes-Heraklion, Latgale, and the East Highlands. Where inequality is considered, however, it is much more common to model it only on an inter-regional level, with a representative household for each nation, for example Berrittella and Zhang (2014) or the well-known GTAP model (Hertel, 2012). Finally, one can use VAR to explore questions surrounding income inequality provided one has a suitable time series on heterogenous households

[62] Randomness does not feature in deterministic models, so, for a given starting point, the model will always produce the same result.

or an inequality index, such as the Gini coefficient[63].

#### 3.3.2.2 Realism of assumptions

Linear or nonlinear processes

As discussed in Section 3.1.3, the economy is a nonlinear system. CGE, DSGE and ABMs are also nonlinear; although linearisation[64] is typically used in DSGEs so that a single, stable equilibrium solution can be found. ABMs do not assume equilibrium and so do not need to linearise nonlinear processes, as the model is run and allowed to develop, rather than solved for a unique solution. CGEs can use nonlinear programming, so do not need to linearise, as, unlike DSGE, they are not stochastic, which makes them simpler to solve. Meanwhile, IOA and VAR are linear models.

Linear models of nonlinear systems, while simple and transparent, will be overly rigid as they cannot reflect the ways in which nonlinear systems can adapt to exogenous changes. For example, IOA assumes fixed production recipes, which is equivalent to firms minimising costs under perfect competition and fixed prices, assuming no technological innovation (Oosterhaven, 1989). This means that, in the event of a shortage of, say, a good used in a given production process, alternative goods or factors of production cannot be used as substitutes. Likewise, in IOA, consumers can't alter their spending patterns and imports cannot increase to compensate for domestic shortages. As such, IOA likely overestimates the consequences of demand and supply shocks, as the modelled economy cannot adapt to mitigate the fallout[65]. CGE, DSGE and ABM models, in contrast, can attempt to model behavioural responses; for example, by incorporating general equilibrium economic theory and data on elasticities.

Nonlinear models, however, are not without their own problems. Mathematising human behaviour, on either the individual or aggregate level, is obviously extremely difficult. The more complicated a model, the more parameters and functional forms must be estimated. This introduces further uncertainty. The behavioural algorithms underpinning ABMs, for example, are frequently hard to validate (Heckbert et al., 2010), particularly as statistical data or econometrically estimated preferences are often available only on an aggregate level. The elasticities used in CGE modelling, similarly, are criticised for not being sufficiently supported by empirical evidence, for example Burfisher (2011). Such problems can occur due to low statistical significance of underlying studies, a

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[63] Inequality indices, including the Gini coefficient, are explained in Section 3.6.

[64] Linearisation gives a linear approximation of a nonlinear function around a given point. It enables linear algebra to then be used to solve the equation, which is faster and simpler than using nonlinear techniques. The approximation, however, is only good very close to the given point.

[65] Although attempts have been made to bypass some of IOA's constricting assumptions, for example, by considering the role of inventories in mitigating supply shocks (Hallegatte, 2014).

lack of studies available on particular goods, and the use of different algebraic forms in the underlying studies compared to the CGE model (Burfisher, 2011). A lack of data has also influenced the choice of model functional forms. For example, it explains the popularity of constant elasticity of substitution functions (Arndt et al., 2002). In addition, CGE and DSGE models are forced to make questionable assumptions to enable a unique stable equilibrium (Grabner, 2014). Such assumptions include only being able to use a restricted set of utility and production functions.

Changing prices and quantities

A further problem with the simplicity of IOA is that it allows either prices or quantities to vary, but not both, which is unrealistic. The other modelling techniques do not have this constraint.

Equilibrium

IOA, CGE and DSGE models assume that markets move from and to general equilibrium. Disequilibrium modelling is far more mathematically challenging (Boland, 2014), and is counter to neoclassical theory. In addition, a non-equilibrium model does not produce a single, steady solution, which makes it harder to draw conclusions or make recommendations. The likelihood of real markets achieving general equilibrium is, however, frequently challenged due to evidence of instability (Cohen and Harcourt, 2003). Many of the assumptions required for general equilibrium are also criticised, including rational expectations and perfect competition; for example, see Boland (2014) or Nachane (2016). Although DSGE models with more realistic market conditions, such as sticky prices or imperfect information, have been solved for general equilibrium; for example, Edge and Gurkaynak (2011). ABMs, meanwhile, don’t solve for equilibrium solutions. While equilibrium could occur, there is no assumption that it does. ABMs instead view economies as complex systems, whose emergent properties cannot be analytically derived, and so solutions cannot be presupposed (Heckbert et al., 2010). Finally, no economic theory underpins VAR, and so no assumption is made about equilibrium.

#### 3.3.2.3 Understanding results

Linear models have the advantage of being simple and transparent. VAR, however, is a statistical, not economic, model, which is generally used to make predictions, and so there is no attempt to discover the economic structure underlying results, i.e. to differentiate between correlation and causation. Therefore, if changes to, say, the agricultural sector were found to have a sizable impact on economic inequality, a VAR model could provide no insight as to *why* this result occurs. Similarly, direct and indirect effects cannot be separated. In contrast, IOA is a structural model where direct and indirect transmission mechanisms between different sectors and institutions in an economy can easily be seen and understood.

ABMs, CGE and DSGE models, meanwhile, feature complex, nonlinear interactions, and so it can be hard to see why results have emerged. ABMs, CGE, and DSGE models are thus often criticized for being 'black boxes' (Grabner, 2014; Topping et al., 2010).

#### 3.3.2.4 Lucas critique

Statistical analysis of historical data, such as VAR, may produce results that are only valid at a given time and situation as, if the policy environment changes, economic agents could adapt their behaviour accordingly, so deviating from past trends. This is known as the 'Lucas critique', and Lucas recommended building bottom-up models of individual behaviour, as these would still be valid in different policy environments (Lucas, 1976). This partly explains the popularity of microfounded DSGE models. DSGEs and ABMs are, in theory, immune to the Lucus critique, as they are bottom-up models of individual behaviour. Such models have, however, been criticised for not being adequately tested against empirical evidence (Wren-Lewis, 2011) and, thus, they can be highly deductive[66]. The usefulness of deductive reasoning is, of course, dependent on the realism of the underlying axioms.

IO and CGE models are based around a SAM for a given year, and thus are strongly influenced by the behaviour of economic actors in that particular year. This is especially an issue for models with many different industries and households, as noise[67] can cancel out when variables are aggregated, so disaggregated data is typically noisier.

#### 3.3.2.5 Demand and supply-side responses to exogenous change

IOA is a demand-driven model. While exogenous supply constraints can be modelled, the only estimated consequences, direct and indirect, stem from the reduced spending by the affected industry on intermediate goods and payments to factors. With CGE, DSGE and ABMs, conversely, the demand and supply side effects of exogenous changes can be modelled simultaneously.

Meanwhile, VAR is used for forecasting, not for modelling counterfactual exogenous changes.

#### 3.3.2.6 Treatment of uncertainty

IOA and CGE models typically do not consider uncertainty, while, as the name implies, DSGE models take a stochastic approach. ABMs are also typically stochastic, as agent's decisions are frequently drawn from PDFs. Meanwhile, VAR uses statistics to estimate confidence intervals, which specify the range of values that one can, to a given percentage degree of confidence, be sure a parameter lies

[66] In deductive reasoning, logic is used to draw conclusions from a series of starting statements, called 'axioms', which are assumed to be true.

[67] Statistical noise is random variation in data, for example, random errors in measurement. The greater the noise, the more variable the data, and the harder it is to make predictions.

within.

3.3.2.7 Dynamic or static

Dynamic models evolve across time, whereas comparative static models only show the equilibrium states of a system before and after a given exogenous change, and so are time independent. IOA and CGE are traditionally static models; although dynamic extensions do exist; for example, Okuyama (2004) and Tang et al. (2016). ABMs, DSGEs and VAR are dynamic, so one can explore how an economy progresses over time and, in the case of DSGE, the path an economy follows to re-establish equilibrium after an exogenous change.

A summary of all the aforementioned characteristics can be found in Table 3.2.

Table 3.2 – Key characteristics of different macroeconomic models

| **Characteristic** | **IOA** | **CGE** | **DSGE** | **ABM** | **VAR** |
|---|---|---|---|---|---|
| Contains multiple industries | Nearly always | Nearly always | Sometimes, but this is not common | Sometimes, but this is not common | Sometimes, but this is not common |
| Includes inequality index or heterogeneous household groups | Frequently | Sometimes, but this is not common | Sometimes, but this is not common | Frequently | Frequently |
| Linear or nonlinear | Linear | Nonlinear | Nonlinear, but often linearised | Nonlinear | Linear |
| Prices and quantities can both change | No – only one or the other can change | Yes | Yes | Yes | Yes |
| Equilibrium assumed | Yes | Yes | Yes | No | No – there is no economic theory in the model |

| | | | | | |
|---|---|---|---|---|---|
| Level of transparency | Very transparent | More black boxed | More black boxed | More black boxed | Transparent, but no attempt to discover causal mechanisms, and cannot separate direct and indirect effects |
| Avoids Lucas critique | No | No | Yes, in theory | Yes, in theory | No |
| Models both supply and demand-side effects of an exogenous change | No – is a demand-driven model | Yes | Yes | Yes | N/A – model is used for predictions, not exploring exogenous changes |
| Treatment of uncertainty | None | None | Stochastic | Stochastic | Statistical confidence intervals |
| Dynamic or static | Comparative statics, although dynamic extensions do exist | Comparative statics, although dynamic extensions do exist | Dynamic | Dynamic | Dynamic |

Notes: Table contrasts key characteristics of input-output analysis (IOA), computable general equilibrium (CGE), dynamic stochastic general equilibrium (DSGE), agent-based models (ABM) and vector autoregressive (VAR) macroeconomic modelling methodologies. Rows in the table are different characteristics. Columns are different models. These attributes indicate that IOA is the most suitable approach to explore the research questions outlined in Chapter 2.

### 3.3.3 Why input-output analysis?

To answer the research questions outlined in Chapter 2, the methodology must be able to explore effects arising from impacts to different economic sectors. While all the modelling types can contain multiple industries, IOA and CGE models are specifically set-up to estimate how different parts of an economy impact on one another. Similarly, to explore questions around income inequality, the modelling framework must also be able to incorporate different household income groups. As seen in the previous section, heterogenous households are possible in all the models; although they are not common in CGE and DSGE.

As this thesis does not attempt to make predictions, but rather is exploring plausible possible mechanisms, tendencies and vulnerabilities, it is crucial that one can understand both which variables are driving results and why these variables have an effect. Intricate mathematics, such as that found in CGE, DSGE and ABMs, can make a model opaque, so, while one can perform a sensitivity analysis and change variables to explore how results in turn alter, it can be difficult to understand why results emerge. Meanwhile, VAR is used for predictions, and so does not attempt to identify causal structural mechanics. The transmission mechanisms in IOA, however, are transparent. One can easily understand why results have emerged, and can also, unlike in VAR, distinguish between direct and indirect effects.

An economy is a nonlinear system, however, VAR and IOA are linear models. This means they cannot reflect the ways in which an economy can adapt to exogenous change. For example, IOA assumes fixed production recipes, which means that alternative goods or factors of production, or increased imports, cannot be used as substitutes for a good that is in short supply. In Chapter 5, SAM time series are used to empirically test how well IOA linear assumptions perform over different time-scales. While the linearity swiftly becomes unrealistic, the model is still found to have reasonable predictive power for approximately a decade, and so can be used to generate plausible scenarios of economic responses to climate change impacts in a given year. Moreover, as discussed in Section 3.1.3, one cannot realistically expect any model to make good long-term predictions about complex nonlinear systems. As explained in Section 3.2, this is why this thesis does not do statistical hypothesis testing, and instead takes a scenario approach to uncertainty.

In addition, while nonlinear models, such as CGE, DSGE[68] and ABMs, are less rigid, the additional parameters and functional forms introduce further uncertainty, and are frequently criticised for being hard to validate. Complexity, thus, does not necessarily add value. Many also argue that more flexible approaches, such as CGE models, are overly optimistic about the extent that economies can

[68] Although, as discussed, DSGE models are frequently linearised to help estimate equilibrium solutions.

adapt to shocks, and so may underestimate economic impacts (Galbusera and Giannopoulos, 2018; Rose, 2004).

Nevertheless, rigidity of fixed production recipes means that IOA likely overestimates economic impacts. It also implies that they are more appropriately used to analyse relatively small demand or supply shocks, not large structural changes[69]. The rigidity of only being able to vary prices or quantities is another disadvantage of the simplicity of IOA but, as demonstrated in Chapter 5, the model empirically still appears to be useful.

Based on the aforementioned criteria, particularly the ability to transparently see causal structural mechanics, combined with the model's empirical performance over short and medium time-horizons, IOA appears to be the most appropriate methodology to address the research questions outlined in Chapter 2. It is ideally placed to model multiple household groups and industries, and to understand how indirect effects ripple across different parts of the network structure of an economy. The linear nature of IOA is not realistic and it models the economy in an excessively rigid way, for example, via fixed production recipes. Empirical analysis in Chapter 5, however, indicates that the model performs reasonably well over short and medium time-scales and so can be used to generate plausible scenarios of economic responses to climate change impacts in a given year. In addition, one should remember that none of the proposed modelling techniques can reliably project out over many decades. The scenario approach taken in this thesis also neutralises the Lucas critique, as the scenarios generated are explicitly viewed as being only a sample of many possible future worlds. There is no claim that the scenarios are *likely* to reflect policy environments in, say, 2100. Similarly, while IOA traditionally does not consider uncertainty, this is not an issue as the thesis is taking a scenario rather than probabilistic approach. The transparency of IOA lends itself to a scenario approach, as one can easily understand why results emerge. While IOA is not dynamic, the research questions in Chapter 2 are focused on new long-run states, not the transitions to these new states, so the static nature of IOA is not troubling. IOA assumes that the economy moves towards a stable equilibrium, which could be unrealistic. IOA's inability to model supply-side responses is also a disadvantage, because the methodology thus models only half of the picture. As has been shown, however, IOA has many significant advantages over the other modelling types, and these are well-suited to address the research questions outlined in Chapter 2. So, for this purpose, IOA's strengths outweigh its limitations.

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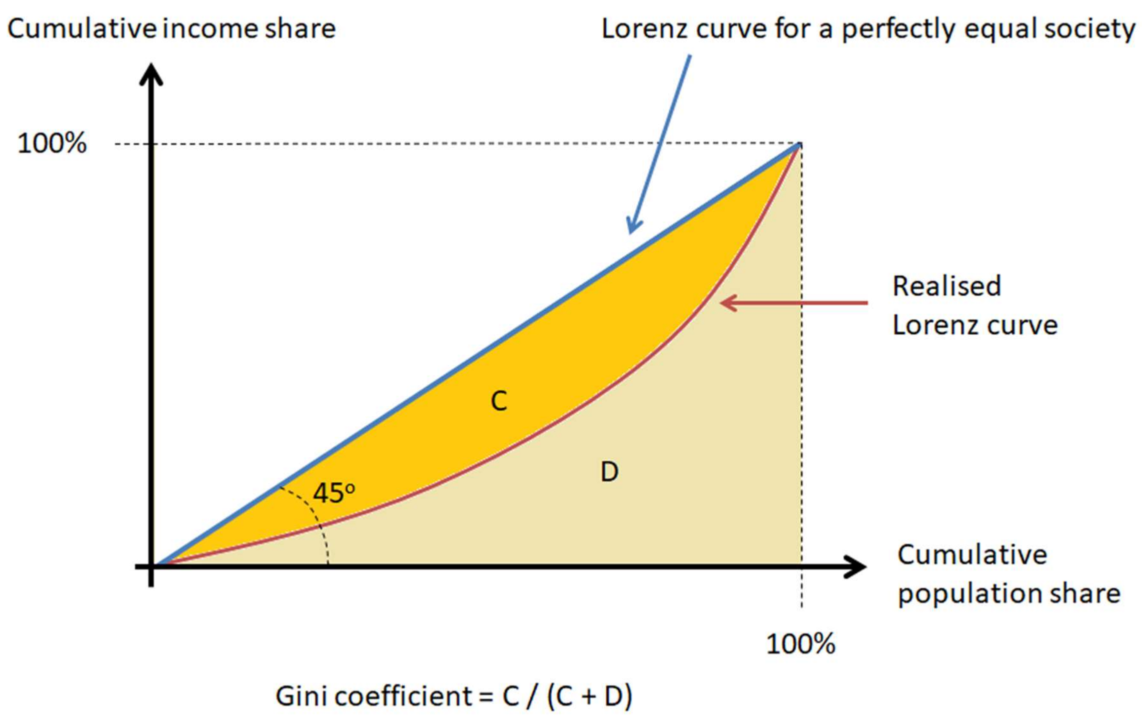
[69] This restriction does not mean that IOA cannot be used to study disasters, as disasters often do not produce large structural changes. As discussed, IOA is a popular tool for disaster impact analysis (Galbusera and Giannopoulos, 2018; Okuyama and Santos, 2014).

## 3.4 Measuring inequality

The final key methodological choice is how income inequality should be measured in this thesis, as there is no single measure of inequality.

An income distribution contains lots of information, which various inequality indices attempt to encapsulate in a single number to enable easy comparison of different distributions. Lots of information is inevitably lost in this process, so all measures of inequality have varying pros and cons. The most appropriate measure of inequality may, thus, vary depending on the specific question being addressed.

Figure 3.1 – Graphical explanation of the Gini coefficient




Notes: The figure shows a graphical representation of the Gini coefficient using a Lorenz curve, which plots cumulative population share against cumulative income share. The Lorenz curve for a perfectly equal society is a line going through the origin at 45°. The Gini coefficient is the ratio of the area between the realised Lorenz curve and the Lorenz curve for a perfectly equal society, C, to the area under the latter, C + D.

The Lorenz curve, which forms the basis of many inequality indexes, plots cumulative population share against cumulative income share. The Gini coefficient, which is the most commonly-used measure of inequality, is the ratio of the area between the realised Lorenz curve and the Lorenz curve for a perfectly equal society[70], to the area under the latter. See Figure 3.1 for a diagram. Assuming that no one has a negative income, the Gini coefficient can vary between 0 and 1.

As the Gini coefficient is derived from income shares, it will not change if all incomes increase by the same factor. This is called 'scale invariance'. In contrast, some common measures of dispersion, such as the range, variance or standard deviation, are not scale invariant. The Gini coefficient also fulfils the 'transfer principle', where a transfer from a higher income person to a lower income person decreases inequality, provided the transfer does not reduce the former's income to below the latter's. Finally, it meets the 'anonymity principle', as it does not matter which particular individuals in a group have which incomes.

To calculate the Gini coefficient, one often estimates the Lorenz curve. This is frequently done by plotting known data points, and then assuming straight lines between these points (Morgan, 1962). One can then estimate the Gini coefficient from areas of trapezia and triangles. As the Lorenz curve is convex, this always leads to the Gini coefficient being underestimated, with the approximation improving as the quantity of available data increases. Parametric estimates are also often used to estimate the Lorenz curve (Schader and Schmid, 1994). Other methods for estimating the Gini coefficient can involve using the covariance of incomes and income rankings, for example, Milanovic (1997), or using the mathematically equivalent expression of the Gini coefficient as half the relative mean absolute difference of all pairs of incomes (Dorfman, 1979). The Gini coefficient is generally more complicated to calculate than other inequality indexes, particularly when dealing with grouped data, such as quantiles (Gastwirth, 1972).

Atkinson (1970) argued that inequality indexes, such as the Gini coefficient, while seemingly providing an objective way to rank different distributions, involve implicit value judgements, and that it would be preferable to transparently state the underlying social welfare function[71] so that it can be debated. Atkinson proposed an index that is scale invariant, and meets the transfer and anonymity principles, but where one can alter an inequality aversion coefficient, $\varepsilon$, to change the weight placed on different parts of an income distribution. The Atkinson index, $A_\varepsilon$, takes the form

$$A_\varepsilon = 1 - \frac{1}{\mu}\left[\frac{1}{n}\sum_{i=1}^{n}(y_i)^{1-\varepsilon}\right]^{\frac{1}{1-\varepsilon}},$$

where $n$, $\mu$ and $y_i$ are the number of people in the population, the mean income, and individual $i$'s income respectively. $\varepsilon$ varies between 0 and 1, and when it is nearer the former or the latter, the index is more sensitive to the wealthiest and poorest ends respectively of the income distribution.

[70] The Lorenz curve for a perfectly equal society is a line going through the origin at 45°.

[71] See Chapter 2 for a definition and discussion of social welfare functions.

The Atkinson index can also be additively decomposed into within group and between group inequalities, and thus can be a more appropriate index than the Gini when dealing with grouped data.

Generalised entropy (GE) measures of inequality are also common, with the Theil T index being particularly popular. The latter takes the form

$$T = \frac{1}{n}\sum_{i=1}^{n}\frac{y_i}{\mu}\ln\left(\frac{y_i}{\mu}\right).$$

Like the Atkinson index, GE measures satisfy scale invariance, the transfer and anonymity principles, and can be additively decomposed. Both the Atkinson and Theil T indexes, however, are not very intuitive. Moreover, as SAMs do not contain information on within-household-group income inequality, the ability to decompose an inequality index into within-group and between-group inequality was not useful for this thesis.

Inequality ratios, such as the ratio of incomes at the 90$^{th}$ and 10$^{th}$ percentiles[72], are also popular, as they are much easier to understand than inequality indices. However, they do not use all the information in an income distribution, as all but two data points are ignored.

While condensing an income distribution down into one number enables ranking of different distributions, the implicit or explicit value judgements required to do this mean the ranking is not objective. As was seen in Chapter 2, collapsing a multi-dimensional problem down onto one-dimension is never value-free. For this thesis, it was thus decided to use inequality ratios, to paint a clear picture of how income distributions evolved, and to allow readers to make their own value judgements about the desirability of different distributions. For example, the Q5/Q1, (Q4+Q5)/(Q1+Q2), Q5/Q3 and Q3/Q1 ratios[73] were estimated in Chapter 6's IAM case study, where Q1 and Q5 were the incomes of the bottom and top income or expenditure[74] quintiles respectively. The ratios allowed changes in inequality between the top and bottom and within the upper and lower halves of the income distribution to be transparently explored, and the ratios collectively used all the information in the SAM income distributions, as would be the case if using an inequality

[72] An income percentile is the value of income below which a given percentage of the population's incomes lie. For example, the 90$^{th}$ percentile is the value of income below which 90% of the population's incomes lie.
[73] While four inequality ratios were calculated, it should be noted that inequality is being captured using three rather than four dimensions, as (Q5/Q3)*(Q3/Q1) = Q5/Q1. Results for all four ratios were quoted to make changes to the different parts of the income distribution explicitly clear.
[74] The Egypt and India SAMs break households down into expenditure deciles. The Ethiopia, Vietnam and Zambia SAMs break households down into expenditure quintiles. The Mexico SAM breaks households down into income deciles. The USA SAM breaks households down into income quintiles.

index. Unlike the latter, however, this collection of ratios is intuitive and does not pretend that an income distribution can objectively be captured by a single number.

## 3.5 Choice of IAM case study

Having established the research questions in Chapter 2, and chosen a scenario analysis approach to uncertainty and IOA modelling of inequality effects earlier in this chapter, one must now consider which IAM is best placed to generate the climate scenarios and associated economic impacts that will form the exogenous changes underpinning the case study in Chapter 6. Similarly, as the research questions require analysis of multiple countries, one must establish the criteria for selecting these countries and then locate appropriate SAMs.

### 3.5.1 Why FUND?

To answer the research questions outlined in Chapter 2, the methodology must be able to explore effects arising from impacts to different economic sectors. FUND is the only IAM to have broken economic impacts down by sector. It would be extremely time-consuming to go through all the impact studies used by another IAM, use these to suggest sector-level damage functions, and then calibrate the latter. FUND is also the model where the most effort has been put into calibrating damage functions for different regions based on region-specific impact studies. Finally, it is relatively transparent, with all the impact studies used clearly listed in its model documentation. One can thus assess FUND’s assumptions and shortcomings more readily than one can for many other prominent IAMs, such as DICE and PAGE.

As such, FUND 3.9, the most recent version of FUND, was used for the IAM case study in Chapter 6.

### 3.5.2 Choice of countries explored in FUND case study

As seen in Chapter 2, existing studies suggest that initial inequality and average income may influence how vulnerable a country is to climate change induced inequality. It was thus important for this thesis to use a sample of economies with a wide range of starting inequalities and overall levels of development. Coastal countries were also desirable, so that the effect of sea-level rise (SLR) could be explored, as were countries from a range of FUND geographical regions, because FUND estimates very different magnitudes of impacts for sectors in different regions.

Table 3.3 – Countries featuring in the FUND case study, their characteristics that demonstrate that they meet the country criteria, and the sourced SAMs that form the basis of each country's analysis

| **Country** | **Year of SAM** | **SAM Gini coefficient** | **2017 GDP per capita (USD)*** | **World Bank income group**** | **Coastal** | **Fund region***** | **SAM source** |
|---|---|---|---|---|---|---|---|
| Egypt | 2010/11 | 0.31 | 2,413 | Lower-middle | Yes | NAF | Al-Riffai et al. (2016) |
| Ethiopia | 2010/11 | 0.33 | 768 | Low | No | SSA | Ahmed et al. (2017) |
| India | 2007/08 | 0.37 | 1,979 | Lower-middle | Yes | SAS | Pal and Bandarlage (2017) |
| Mexico | 2008 | 0.44 | 8,910 | Upper-middle | Yes | CAM | Jemio et al. (2015a) |
| United States | 2016 | 0.43 | 59,928 | High | Yes | USA | SAM was constructed in this thesis, as described in Chapter 4 |
| Vietnam | 2007 | 0.34 | 2,342 | Lower-middle | Yes | SEA | Arndt et al. (2014) |
| Zambia | 2007 | 0.55 | 1,513 | Lower-middle | No | SSA | Chikuba et al. (2013) |

** From* World Bank (2019a)*. ** From* World Bank (2016b)*. *** See Anthoff and Tol (2014b) for the full list of countries in each FUND region.*

Notes: The table details the seven countries that feature in the FUND case study in Chapter 6, along with the year of the sourced SAM that will form the basis of that country's analysis, the Gini coefficient indicated by this SAM, the 2017 GDP per capita in the country, the World Bank income group in which the country is classified, whether or not the country is coastal, the FUND geographical region the country is in, and the reference to the study where the sourced SAM can be found. The Gini coefficient is the most commonly used inequality index. It is described in Section 3.4 of this chapter.

Table 3.3 lists the countries that were explored in the FUND case study. According to World Bank data for all countries, the average inequality Gini coefficient for a country between 2008 and 2016 ranged from 0.25 (the Ukraine) to 0.63 (South Africa). From Table 3.3, one can that see that the countries explored in the FUND case study span 63% of this range, so the case studies include countries with a wide range[75] of starting levels of inequality. All four World Bank country income groups, high, upper-middle, lower-middle and low, are also represented in the set of countries studied, as are coastal countries and six FUND geographical regions. A suitably disaggregated[76] existing SAM could not be found for a high-income country, so one[77] was constructed from scratch for the United States (US). The US was chosen above other high-income countries because it is one of the wealthiest countries in the world by GDP per capita, is currently relatively unequal compared to most of the other countries featuring in the study, is coastal, and is from a FUND geographical region that would not otherwise feature in the study. It also has readily available, reliable data.

## 3.6 Choice of impact studies case study

Finally, the subject of the impact studies case study had to be chosen. An area with potentially large and diverse impacts from climate change was needed, as such a place could conceivably see significant changes in inequality from global warming.

Mean near-surface warming near the Earth's poles has occurred at twice the rate as warming at

[75] The whole range is not spanned because suitable SAMs could not be found for countries at the extremes of the range. In addition to being sufficiently disaggregated, SAMs had to be considered reliable. This project thus used only SAMs created in this thesis, SAMs produced by government agencies or the International Food Policy Research Institute (IFPRI), or SAMs presented in peer-reviewed papers. The IFPRI runs the Nexus Project, which aims to build high quality SAMs to calibrate CGE models. The project was launched to improve transparency and consistency between SAMs, and it has assembled a large number of SAMs for lower-income countries. SAMs published in peer-reviewed journals, for example, Diao et al. (2012), and produced by national statistics offices, for example, IFPRI and CAPMAS (2016), are part of this project. United Nations institutions, such as the Food and Agriculture Organization of the United Nations (FAO) and the International Fund for Agricultural Development help deliver the Nexus project, and IFPRI SAMs have been sponsored by the World Bank; for example, see IFPRI (2015). It was consequently deemed a trustworthy source. As a final check that only reliable SAMs were used, key macroeconomic data, such as GDP, the main sectors contributing towards GDP, and the Gini coefficient, were taken from the SAMs and compared to national statistics and World Bank Gini estimates (World Bank, 2016a) to check that that SAMs were consistent with reputable macroeconomic statistics.

[76] In addition to having disaggregated household accounts, to meaningfully explore drivers of inequality a SAM must also have sufficiently disaggregated factors of production accounts. If the labour account, say, is not disaggregated, for example, by the educational-level of workers, then household groups will receive a fixed percentage of any new wages, regardless of which industry has generated these wages. This is a very incomplete picture of the drivers of inequality in an economy (Pieters, 2010).

[77] As the US SAM was constructed from scratch from national statistics data that was available in time-series, a time-series of three SAMs, for 2003, 2010 and 2016, could thus be relatively quickly constructed. This series was then used in Chapter 5, along with two existing SAM time-series, to test the assumptions underpinning IOA and to inform which accounts should be exogenous in the model.

more central latitudes (Cohen et al., 2014). The Arctic and Antarctic are thus likely to experience more severe climate change than the rest of the globe. While there is no significant economy in Antarctica, Arctic economies are particularly linked to the environment and natural resources (Berman and Schmidt, 2019), and the effects of global warming could vary considerably from sector-to-sector. For example, ships with ice-breaking capabilities are expensive, and so Arctic shipping and fishing are only economically viable in ice-free waters. Loss of sea ice is thus expected to open up more Arctic shipping routes (Smith and Stephenson, 2013). The Arctic seabed is also thought to be rich in undiscovered minerals, oil and gas (Gautier et al., 2009). In addition, industrial activities in the Arctic give rise to local production networks (Stephenson and Agnew, 2016), and such infrastructure and supporting settlements would probably expand to facilitate increased industry.

There are, however, also likely to be large costs to Arctic economies from climate change. For example, as permafrost thaw damages infrastructure (Melvin et al., 2017), sea-level rise and increased coastal erosion jeopardises communities (Berman and Schmidt, 2019), more intense Arctic cyclones cause disruption (Day et al., 2018), and subsistence activities, such as hunting, are affected by impaired ecosystems (Markon et al., 2012).

Finally, it is unclear whether some sectors will likely benefit or suffer. For example, the central Arctic Ocean, currently protected by ice, may be an abundant source for fisheries (Hoag, 2017), and warmer Arctic oceans and reduced sea ice might boost primary production[78] through photosynthesising phytoplankton (Park et al., 2015), which, in turn, could increase Arctic fish stocks. On the other hand, as a result of reduced sea-ice, Arctic oceans may absorb more $CO_2$, and thus become more acidic (Thor et al., 2018), which could undermine calcifying species (Lischka and Riebesell, 2012), such as pteropods, mussels, and clams. In addition, changing ocean temperatures could lead to fish migrating from lower latitudes to higher latitudes, with invasive species possibly disrupting existing species (Frainer et al., 2017). Similarly, while climate change may increase the agricultural growing season in the Arctic, it could also dry out the soil (Markon et al., 2012). The likely effects on tourism are also debated, as warming could increase summer tourism opportunities but decrease winter ones (Yu et al., 2009).

Different economic sectors in the Arctic may, thus, see large and diverse impacts from climate change, which could, in turn, have large and diverse economic impacts on different households. To explore this, an Arctic economy was chosen for the impact studies case study.

[78] Primary producers use photosynthesis and chemosynthesis to make carbon compounds from $CO_2$. Examples include phytoplankton, such as algae and photosynthesising bacteria. Primary producers are the foundation of aquatic ecosystems.

The US provides extensive economic data on a state-by-state basis, far more so than, say, Russia or Norway do for their internal regions. There is also an existing suitable SAM for Alaska (Seung, 2014), while one couldn't be found for Arctic regions in any other country. In addition, there are impact studies covering many different sectors in Alaska.

As one can see from Table 3.3, while all World Bank country income groups are represented in the FUND case study, five of the seven countries that feature are low or lower-middle income. Alaska's GDP per capita in 2017 was USD 71,274, even higher than the US average of USD 59,928. As the US was the wealthiest country in the FUND case study, Alaska's inclusion in this thesis improves representation of the upper end of the global income distribution. This was an additional benefit, as the literature review in Chapter 2 suggested that average income may influence how vulnerable a country is to climate change induced inequality.

## 3.7 Summary

This chapter explained the main methodological and subject choices made in this thesis.

Firstly, it introduced the different types of IAMs, and explained that IAMs that specialise in estimating the economic impacts of changes in climate variables will be explored in this thesis. Common criticisms of these types of IAMs were then presented, including concerns around discounting, equity weights, commensurability, uncertain climate projections and damage functions, and the inherent difficulties of testing counterfactual models. Much of the criticism stems from these IAMs' use of CBA, which is not a tool used in this thesis. Nevertheless, in light of the high levels of uncertainty in the model and the difficulties, in general, of modelling complex nonlinear systems over long periods of time, this thesis does not attempt to make predictions, do statistical hypothesis testing, or run Monte Carlo simulations. It instead takes a scenario approach to uncertainty, to get an idea of the range of outcomes that may occur. The focus will be on exploring tendencies and the factors driving them, seeing if any persuasive patterns emerge, and putting forward qualitative propositions. The IPCC SRES and RCP scenarios will be used.

To decide which methodology is most appropriate to extend IAMs and impact studies so that they can estimate the impact of climate change on income inequality, and so address the research questions outlined in Chapter 2, this chapter then reviewed the main tools currently used for macroeconomic modelling and compared their key characteristics, strengths and weaknesses. This review suggested that IOA should be used in this thesis, as it is well placed to model multiple industries and households, and to understand how indirect effects ripple across different parts of the network structure of an economy. Different common ways of measuring inequality were then presented, and it was argued that inequality ratios are transparent and allow readers to make their own value judgements about the desirability of different distributions. Inequality ratios will thus be used to measure inequality in this thesis.

Given the research questions outlined in Chapter 2, it was then explained that FUND is the most appropriate IAM to be used for the IAM case study in Chapter 6. Criteria for choosing which countries were the focus of this study were subsequently outlined by drawing upon the literature review in Chapter 2, and SAMs for appropriate countries were identified. Finally, Alaska, an area with potentially large and diverse impacts from climate change that could conceivably produce significant changes in inequality, was chosen to be the subject of the impact studies case study in Chapter 7.

# Chapter 4 – The Social Accounting Matrices (SAMs)

This chapter describes the compilation and adaptation of social accounting matrices (SAMs) needed for the case studies. Section 4.1 introduces input-output tables (IOTs) and SAMs, and how they are generally constructed. Section 4.2 described the algorithmic and residual methodologies that are typically used to balance SAMs, and explains and justifies the balancing procedures used in this thesis. Section 4.3 documents the construction of the United States (US) SAMs that are used to empirically test input-output analysis (IOA) assumptions in Chapter 5, and in the IAM case study in Chapter 6. Section 4.4 explains adaptations made to existing SAMs for other countries that form part of the IAM case study in Chapter 6, and to an existing Alaskan SAM, which is needed for the impact studies case study in Chapter 7.

## 4.1 Introduction to SAMs

### 4.1.1 What are input-output tables (IOTs) and social accounting matrices (SAMs)?

IOTs map inter-industry monetary flows over a given time period, usually a year. The manufacturing sector, for example, may need to buy energy to enable production. Similarly, the agricultural industry may need manufactured products, such as tractors, to help cultivate and harvest crops. IOTs track such purchases, and also document consumption from institutions, such as households, government and the rest of the world (ROW). The inter-industry purchases, referred to as 'intermediate demand', are compiled into a square matrix whose elements represent monetary flows from the column industries to the row industries. Meanwhile, value added, total output, and institutional consumption, which is traditionally called 'final demand', are defined as vectors. Figure 4.1 shows a typical IOT layout.

Figure 4.1 – A typical IOT layout

<table>
<tr><th></th><th>Industry 1</th><th>Industry 2</th><th>Households, government and rest-of-the-world (ROW)</th><th>Total output</th></tr>
<tr><td>Industry 1</td><td colspan="2" rowspan="2">Intermediate demand</td><td rowspan="2">Final demand</td><td rowspan="2">Total output</td></tr>
<tr><td>Industry 2</td></tr>
<tr><td>Value-added</td><td colspan="2">Indirect taxes, compensation of employees and retained earnings</td><td></td><td></td></tr>
<tr><td>Total output</td><td colspan="2">Total output</td><td></td><td></td></tr>
</table>

Notes: The figure shows the constituent parts and layout of a typical input-output table (IOT). Column accounts make payments to row accounts. The payments an industry makes to other industries plus indirect taxes, compensation of employees that it pays and retained earnings must be equal to payments it receives from other industries, households, government and the rest of the world (ROW).

SAMs continue this accounting procedure of mapping flows over the course of a year from column to row sectors, but provide a more complete picture of an economy. They are square matrices that typically include factors of production and the capital account, in addition to the usual industries, commodities and institutions. As they are square matrices, they contain information on flows between institutions, such as direct taxes and benefits, and value-added payments to institutions, such as wages and profits. SAMs thus capture the expenditure-production-income circular flow around an economy more comprehensively than an IOT. SAMs also often disaggregate households into different groups, so one can show, for example, households with different levels of income having different consumption patterns and sources of income. Figure 4.2 shows a typical SAM layout.

Figure 4.2 – A typical SAM layout

| | | Commodities | Activities | Factors | Current account: Households | Current account: Enterprises | Current account: Government | Capital account | Inventories | ROW | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Commodities | | | Intermediate output | | Household consumption | | Government consumption | Investment | Change in inventories | Exports | Total demand |
| Activities | | Domestic supply | | | | | | | | | Activity income |
| Factors | | | Value-added at factor cost | | | | | | | Factor income from abroad | Total factor income |
| Current account | Households | | | Wages | Transfers | Distributed profits | Benefits | | | Transfers from abroad | Household income |
| | Enterprises | | | Private non-labour income | Transfers | Transfers | Transfers | | | | Enterprise income |
| | Government | | Indirect taxes less subsidies | Factor payments to government | Income taxes | Corporation tax | Federal transfers to local government | | | | Government income |
| Capital account | | | | | Savings and fixed capital consumption | | | | | Capital transfers from abroad | Capital income |
| Inventories | | | | | | | | Change in inventories | | | Change in inventories |
| ROW | | Imports | | Factor income sent abroad | Transfers abroad e.g. remittances | | | Capital transfers abroad | | | Foreign income |
| | | Total supply | Gross output | Total factor expenditure | Household savings and expenditure | Enterprise savings and expenditure | Government savings and expenditure | Capital expenditure | Change in inventories | Foreign outlays | |

Notes: The figure shows the constituent parts and layout of a typical social accounting matrix (SAM). Column accounts make payments to row accounts. Grey cells contain no payments. Column totals must be equal to row totals to ensure that all spending and saving is financed.

### 4.1.2 How SAMs are constructed

Constructing a SAM is a large undertaking as they are extremely data-intensive. The first frameworks for constructing SAMs were provided by Richard Stone (Stone and Brown, 1962), the World Bank (Pyatt and Round, 1977) and Keuning and Ruuter (1988), while more recent manuals on SAM construction include Pyatt (1991), Round (2003) and Breisinger et al. (2009). In addition, the UN System of National Accounts advises on compiling national statistics and encourages similar practices across different countries, along with the collection of data, such as 'make-matrices', that are useful for building IOTs and SAMs.

When constructing a SAM, one typically starts by compiling a highly aggregated SAM, called a 'macro-SAM', where, for example, all industries are aggregated into a single industries account, and all household groups and different factors are combined into respective households and factors accounts. Figure 4.2 is an example structure for a macro SAM.

For a SAM to be internally consistent, the money flowing into an account over a year must be equal to the money flowing out of that account over the year. This ensures that all spending and saving is financed, and that money does not appear from nowhere or vanish into the ether. When this condition is fulfilled, a SAM is said to be 'balanced'.

One must draw upon data from a variety of sources when building a SAM. Typical sources include national statistics, government reports, household and business surveys, and central bank data. Discrepancies are often found between estimates of an element from different sources due to differences in estimation procedures, slightly different classification schemes or exchange rates, and omissions or errors. As detailed in the following section, algorithmic or residual techniques are then used to balance a SAM; although judgements can also be made about which source is more reliable (Round, 2003).

Each element in a macro-SAM represents a matrix of flows between disaggregated accounts; for example, interindustry purchases or consumption flows from households to commodities. So after assembling a macro-SAM, one typically disaggregates all macro-SAM elements into their underlying matrices to create a 'micro-SAM'[79]. This typically uses weights derived from survey data. Each submatrix in the micro-SAM will be equal to its corresponding element in the macro-SAM. Algorithmic or residual techniques are then used to balance the micro-SAM.

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[79] One could build a micro-SAM without a macro-SAM; however, this is relatively uncommon, as aggregate macroeconomic statistics are typically more confidently known than disaggregated data (Hubic, 2012).

## 4.2 Balancing SAMs

### 4.2.1 Algorithmic balancing

One typically knows what the row, $u_i$, and column, $v_j$, totals should be, but has a raw matrix, $\boldsymbol{Z}(0)$, with elements $z_{ij}(0)$ describing the monetary payment by account $j$ to account $i$, that doesn't generate those row and column totals. There are many different matrices that could generate $u_i$ and $v_j$. So which estimate, $\widetilde{\boldsymbol{Z}(1)}$, of the true matrix, $\boldsymbol{Z}(1)$, should one choose? The standard approach is to define a matrix of 'technical coefficients', $\boldsymbol{A}(0)$, with elements $a_{ij}(0)$ describing the monetary payment by account $j$ to account $i$, per unit of account $j$'s total expenditure, such that $\boldsymbol{A}(0) = \boldsymbol{Z}(0)\widehat{\boldsymbol{x}}^{-1}$, where $\boldsymbol{x}$ is a vector of respectively ordered known account totals, $x_j$, $\widehat{\boldsymbol{x}}$ is a diagonal matrix with the elements of $\boldsymbol{x}$ forming its main diagonal, and $\widehat{\boldsymbol{x}}^{-1}$ is its inverse. One then uses linear or nonlinear optimisation to find a new estimated matrix, $\widetilde{\boldsymbol{A}(1)}$, with corresponding elements $\widetilde{a_{ij}(1)}$, which satisfies known constraints whilst minimising the deviation from the $\boldsymbol{A}(0)$. There are, however, many different measures of closeness one could minimise.

Let us explore the most popular measures.

#### 4.2.1.1 Linear and quadratic closeness measures

Quadratic measures of closeness, such as $\sum_i \sum_j \left[a_{ij}(0) - \widetilde{a_{ij}(1)}\right]^2$, penalise larger deviations over smaller ones, whereas linear measures, for example $\sum_i \sum_j \left|a_{ij}(0) - \widetilde{a_{ij}(1)}\right|$, give all deviations equal weight. Both quadratic and linear techniques do not necessarily protect the signs of coefficients, which is problematic, as economic flows are unlikely to suddenly reverse direction. One can, however, achieve this by adding $m \times m$ $\widetilde{a_{ij}}(1) \geq 0$ constraints, where $m$ is the number of elements in a column or row, having moved elements within the $\boldsymbol{Z}(0)$ matrix before generating $\boldsymbol{A}(0)$ and running the balancing programme, so that a negative value at $z_{ij}(0)$ is removed, multiplied by -1, and then added to $z_{ji}(0)$. If account A pays account B -£x, for example, this entry could be moved within the matrix so that B instead pays A £x. With these additional constraints, programming must be used to minimise even quadratic measures of closeness, as an optimisation problem with inequality constraints cannot be solved analytically.

Many different linear and quadratic approaches have been proposed for minimising the deviation of $\widetilde{\boldsymbol{A}(1)}$ from $\boldsymbol{A}(0)$ subject to $\sum_j \widetilde{a_{ij}(1)}x_j = u_i$, $\sum_i \widetilde{a_{ij}(1)}x_j = v_j$, and $\sum_i \widetilde{a_{ij}(1)} = 1$. The relative squared deviation, $\sum_i \sum_j \frac{[a_{ij}(0) - \widetilde{a_{ij}(1)}]^2}{a_{ij}(0)}$, for example, allows for greater variation in larger coefficients, and the relative absolute deviation, $\sum_i \sum_j \frac{|a_{ij}(0) - \widetilde{a_{ij}(1)}|}{a_{ij}(0)}$, has also been used. Similarly, to prioritise reducing changes in larger elements, which typically have greater input-output analysis (IOA) multiplier effects[80], the weighted squared deviation or weighted absolute deviation can be used. Here the deviations are multiplied by the base coefficient, for example, $\sum_i \sum_j a_{ij}(0)\left|a_{ij}(0) - \widetilde{a_{ij}(1)}\right|$. Sometimes, instead of using the base coefficients as weights, the latter can reflect subjective assessments of the accuracy of starting coefficients.

#### 4.2.1.2 Information gain

'Information', as introduced by Hartley (1928), is a measure of the uncertainty that is resolved when one of many possible messages is received. It is therefore dependent on the probability, $p_k$, that message $k$ occurs. Logarithms lend themselves to measuring information. The logarithm power rule, $\ln(\mathrm{s}^{\mathrm{n}}) = \mathrm{n}\ln(\mathrm{s})$, for example, means that the information contained in rolling a dice three times will be equal to three times the information contained in rolling that dice once. Similarly, the logarithm power rule, $\ln(\mathrm{AB}) = \ln(\mathrm{A}) + \ln(\mathrm{B})$, means that the information contained in flipping a coin and rolling a dice will be equal to the information contained in flipping a coin plus the information contained in rolling a dice. Finally, $\ln(\mathrm{x})$ is a continuous, monotonically increasing function, so the more surprising an event, the higher its information content. Shannon (1948) proved that the logarithm was the only function that had these necessary properties, so information is defined to be $-\ln(p_i)$. As $p_i \leq 1$, the negative logarithm is used so that information is not negative.

'Information entropy' or 'Shannon entropy', $H$, as defined by Shannon (1948), is the expected information content of a message transmitted by a source from among multiple possible messages. Specifically, $H = -\sum_i p_i \ln(p_i)$. Imagine that one has an estimate, $q$, of a true probability distribution, $p$. If the information coding system is designed for $q$ instead of $p$, then the information received is based upon $q$, but the actual probability that a message occurs will still be $p$. The expected information content, $H(p,q)$, will thus be $H(p,q) = -\sum_k p_k \ln(q_k)$. This is called the 'cross-entropy' between $p$ and $q$. The error introduced by calculating the cross-entropy instead of the actual entropy of the probability distribution $p$ is called the 'Kullback–Leibler divergence', $D_{KL}(P||Q)$, where

$$D_{KL}(P||Q) = -\sum_k p_k \ln(q_k) - \left(-\sum_k p_k \ln(p_k)\right) = \sum_k p_k \ln\left(\frac{p_k}{q_k}\right).$$

This is the expected increase in information required to communicate messages when the coding system has been designed for an approximation of the actual probability distribution. The Kullback–

[80] See Chapter 5 for an explanation of multiplier effects.

Leibler divergence, which is also never negative, is often called the 'information measure of distance'.

As a SAM is a table of inputs which can be expressed as percentages of each sector's output, Theil (1967) noted that this is analogous to a joint probability distribution, and so information theories can be applied. For example, for balancing a SAM, the information divergence will be

$$D_{KL}(\widetilde{\boldsymbol{A}(1)}||\boldsymbol{A}(0)) = \sum_i \sum_j \widetilde{a_{ij}(1)} \ln\left(\frac{\widetilde{a_{ij}(1)}}{a_{ij}(0)}\right).$$

One is then seeking the $\widetilde{\mathrm{A}(1)}$ that minimises $\mathrm{D_{KL}}(\widetilde{\mathrm{A}(1)}||\mathrm{A}(0))$, under the constraints

$\sum_{\mathrm{j}} \widetilde{a_{ij}(1)}x_{\mathrm{j}} = \mathrm{u_i}$ and $\sum_i \widetilde{a_{ij}(1)}x_j = v_j$. Using a Lagrangian function[81], $D_{KL}(\widetilde{\boldsymbol{A}(1)}||\boldsymbol{A}(0))$ can be minimised to give $\widetilde{a_{ij}(1)} = r_i a_{ij}(0)s_j$, or

$$\widetilde{\boldsymbol{A}(1)} = \hat{\boldsymbol{r}}\boldsymbol{A}(0)\hat{\boldsymbol{s}},$$

where

$$r_{ij} = \begin{cases} \frac{u_i}{\sum_j a_{ij}(0)s_j} & if\ i = j \\ 0 & if\ i \neq j \end{cases}, \quad s_{ij} = \begin{cases} \frac{v_j}{\sum_i r_i a_{ij}(0)} & if\ i = j \\ 0 & if\ i \neq j \end{cases},$$

and $r_{ij}$ and $s_{ij}$ are the components of the diagonal matrices $\hat{\boldsymbol{r}}$ and $\hat{\boldsymbol{s}}$ respectively. One can then iteratively solve for $\hat{\boldsymbol{r}}$ and $\hat{\boldsymbol{s}}$. This popular process, known as 'RAS', was introduced by Stone (1961). Note that as $\hat{\mathbf{r}}$ and $\hat{\mathbf{s}}$ will always be positive, the RAS approach preserves the signs of coefficients.

One can add more constraints if desired; for example, to ensure that a submatrix of a micro-SAM sums to the equivalent element in the macro-SAM. With additional constraints, however, one can no longer use RAS iteration and must instead use nonlinear programming. In such cases, to avoid undefined limits arising from zeros, one typically lets $a_{ij} = a_{ij} + \delta$, where $\delta$ is a very small positive number (Robinson et al., 2001).

### 4.2.2 Residual accounts

Different parts of a SAM are often known with different levels of confidence. The Federal Reserve, say, does not collect data on household changes in assets and liabilities in its Financial Accounts of the United States (FED, 2018a). Changes in household positions are instead assumed to be changes in total assets and liabilities less changes in government, business and ROW positions. Many SAM builders, similarly, take the most uncertain account to be a residual account that balances the SAM. Pyatt (1991) and IMPLAN (Cheney, 2018), for example, take this approach and make the

[81] See Miller and Blair (2009) for the full derivation.

savings/capital account residual, while Jemio et al. (2015b) lets the enterprise current account be a residual. Residual accounts are then typically assumed to be exogenous in any IOA, i.e. they are determined outside of the model and so do not contribute towards multiplier effects. It is also common to use a residual account to balance a macro-SAM and then use algorithmic techniques to balance the micro-SAM. This approach is taken, for example, by Ahmed et al. (2017), Randriamamon and Thurlow (2016), and Thurlow and Van Seventer (2016).

The advantage of using a residual account is that one preserves the elements one has confidence in and that are important to the study. One is only altering exogenous accounts that, by definition, will not be a focus of subsequent IOA. Moreover, values produced by national statistics offices are not altered by algorithms that frequently do not have economic justification.

### 4.2.3 Chosen balancing methodology

Which balancing methodology is the best? This is difficult to answer as the 'true' balanced underlying economy is unknown, and tests that take a balanced matrix, unbalance it, and then see which technique gets closest to the prior balanced matrix are inherently biased by the measure of closeness chosen to assess errors. An entropy-distance measure of error, for example, will find that an entropy-distance minimising algorithm performs best.

Papers typically provide no economic justification for algorithmically balancing SAMs or the choice of algorithm. Information-distance minimisation techniques, however, are very popular (Round, 2003). If a SAM is only slightly unbalanced, then thankfully only small differences typically emerge when using different algorithmic balancing techniques (Round, 2003).

For this thesis, residual accounts were used to balance the US macro- and micro-SAMs, as described in the subsequent section. This ensured that the US National Income and Product Accounts (NIPA) data used to construct the macro-SAMs was preserved. It also meant that survey data used to disaggregate crucial submatrices in the micro-SAMs would not be arbitrarily adjusted. As a statistical discrepancy forms part of the NIPAs, this was given its own account in the SAMs, and balancing adjustments took place here. The account was then assumed to be exogenous to the model in all subsequent IOA[82], so it did not influence results. The adjustments required to balance both the macro- and micro-SAMs in all cases summed to the statistical discrepancy quoted for that year in the NIPAs.

Sometimes, using two different surveys to disaggregate a macro-SAM element, or using the same survey in different ways, would occasionally produce different results. In such cases, the RAS

[82] The IOA models are described in Chapter 5.

procedure was, however, used to reconcile the different survey results by adjusting the less confidently known disaggregated sub-matrix elements to the more confidently known submatrix row and column totals. Such instances are clearly indicated in Appendix D and, as discussed, such reconciliation procedures are common in SAM construction.

As described in section 4.4, the Alaska-SAM (Seung, 2014) required further disaggregation and then rebalancing. Existing residual elements were used for the latter. In addition, the RAS procedure was used to reconcile survey results with known submatrix row and column totals, so that all the data in the original peer-reviewed Alaskan SAM was preserved. All such instances are clearly indicated in section 4.4.

## 4.3 Constructing US SAM time-series

The Bureau of Economic Analysis' NIPAs provide extensive national accounting data, with historical data available from the Federal Reserve Economic Data (FRED) database (FED, 2018b). As time-series could thus be obtained, it was decided that a time-series of US SAMs, for 2003, 2010 and 2016, should be compiled to empirically test the extent that useful lessons for a country's future might be learnt from an IOA of a recent SAM[83]. This analysis can be found in Chapter 5, and it was also used to guide which accounts were assumed to be exogenous to the model in the IOA in Chapters 6 and 7.

As compiling SAMs is highly time and data intensive, very few SAM time series currently exist. Constructing such a time-series was, thus, a useful extension, and a methodological contribution to IOA, as such empirical tests could hitherto only be found for IOT, not SAM, time-series.

### 4.3.1 US macro-SAMs

The NIPA 'selected tables' (BEA, 2018a) clearly show how the different NIPA components are combined to get balanced accounts. These national accounting identities were followed to construct the US SAMs. Figure 4.3 shows the codes used in this thesis to label the different elements in the US macro-SAMs, and Appendix D details the data series title(s) and source database(s) used to compile each element.

The statistical discrepancy in the NIPAs arises from the different methodologies used to estimate gross domestic product (GDP) and gross domestic income (GDI). Theoretically, these should be equal. In practice, however, they are always slightly different, as they are compiled using the

[83] Earlier SAMs were not compiled, as some data series changed in 2003, so SAMs before and after this year would not be directly comparable.

expenditure and income approaches respectively. The same statistical discrepancy also features in the savings and investments component of the NIPAs, because gross saving is estimated as part of the income method, while capital account expenditures are estimated as part of the expenditures approach.

Figure 4.3 – Codes for each SAM element

| | | | | | Current account | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | **Commodities** | **Industries** | **Factors** | **Households** | **Enterprises** | **Government** | **Inventories** | **Statistical discrepancy** | **Capital accounts** | **ROW** | **Row totals** |
| **Commodities** | | | I1 | | Hcur1 | | Gcur1 | Inv | Sd | Cap1 | R1 | Tcom |
| **Industries** | | C1 | | | | | | | | | | Tind |
| **Factors** | | | I2 | | | | | | | | R2 | Tfac |
| Current account | **Households** | | | F1 | | Ecur1 | Gcur2 | | | | R3 | Thcur |
| | **Enterprises** | | | F2 | Hcur2 | | Gcur3 | | | | R4 | Tecur |
| | **Government** | | | F3 | Hcur3 | Ecur2 | | | | | R5 | Tgcur |
| **Inventories** | | | | | | | | | | Cap2 | | Tinv |
| **Statistical discrepancy** | | | | | | | | | | Cap3 | | Tsd |
| **Capital account** | | | | | Hcur4 | Ecur3 | Gcur4 | | | | | Tcap |
| **ROW** | | C2 | | F4 | Hcur5 | Ecur4 | Gcur5 | | | Cap4 | | Trow |
| **Column totals** | | Tcom | Tind | Tfac | Thcur | Tecur | Tgcur | Tinv | Tsd | Tcap | Trow | |

Notes: Figure shows the codes used in the chapter text to refer to the different elements of the US SAMs. Grey cells without labels are not populated in the SAM and so are not assigned codes. Appendix D details the data series title(s) and source database(s) used to compile each element.

Two elements, intermediate consumption (I2) and gross operating surplus (F2), are not explicitly estimated as part of the NIPAs, but are the residual of data, so could easily be calculated. In addition, a few account totals are not explicitly estimated in the NIPAs, but could be calculated by summing together the relevant NIPA elements. For example, the household current account total (Thcur) was equal to personal income plus household consumption of fixed capital, contributions for government social insurance and transfer receipts from ROW to persons. The two latter components had to be added on as personal income in the NIPAs includes the net of these payments, whereas the SAM required gross flows. All such calculations are detailed in Appendix D.

The NIPA breakdown of different receipts and payments between households, enterprises and government is comprehensive, with the exception of interest payments and receipts. These are given as totals for each institutional account, but the NIPAs do not specify, for example, how receipts from personal interest payments are split between the government and enterprises current accounts. As total interest payments and receipts to and from each institutional account are known, one is faced with six unknowns and six equations, so the system can be solved simultaneously.

The determinant of the matrix of coefficients is, however, zero, so the system has infinite or non-existent solutions. As a solution was subsequently found, one was dealing with the former. Household and enterprise balance sheet data from the Federal Reserve's Financial Accounts of the United States were used to choose a solution[84]. Specifically, the ratio of household and enterprise holdings of government debt and municipal securities in each relevant year was used as the ratio to split government interest payments to persons and business between the household and enterprise current accounts. All other interest payments could then be determined from the simultaneous equations.

The produced macro SAMs were very slightly imbalanced due to rounding errors in NIPA data. These errors were extremely small in all cases. The largest deviation of a row or column sum from its total amounted to 0.00023%. Most of the errors were much smaller, with the average error across all SAMs being 0.00001%. As discussed, the statistical discrepancy account was used as a residual to correct these imbalances. The account total was still equal to the quoted statistical discrepancy in the NIPAs.

The balanced US macro-SAMs for 2003, 2010 and 2016 can be found in Appendix E.

### 4.3.2 US micro-SAMs

The US macro-SAMs were disaggregated into 73 commodities, 71 industries, 71 value added

[84] Leung and Secrieru (2012) similarly use balance sheet data to estimate how property income payments are split across institutions when building a Canadian SAM.

accounts, and five household accounts. With the additional accounts for enterprises, government, inventories, capital, ROW and statistical discrepancies, the micro-SAMs are 226 × 226 matrices. Appendix F provides a full list of the micro-SAM accounts. The level of disaggregation was determined by data availability. The number of commodities and industries accounts, for example, was determined by the number of commodities and industries categories in the Bureau of Economic Analysis' (BEAs') make (BEA, 2018b) and use (BEA, 2018c) tables. Similarly, households were broken-down into income-quintiles as much of the required household survey data was available at this level.

Appendix D lists the data used to disaggregate each macro element. All these sources indicated the proportions by which the relevant macro-SAM element was broken-down. As is usual with SAM compilation, the macro-SAM elements were thus preserved, as one has greater confidence in national accounts data than other survey data.

A few surveys were not available on an annual basis, and so disaggregation used data from the survey closest to the SAM year. The BEA's data on value-added data from US direct investment abroad broken-down into different industries (BEA, 2018d), for example, was used to disaggregate R2, but was only available from 2009 onwards. So R2 in the 2003 SAM was disaggregated using 2009 proportions. This was a reasonable approximation, as the average standard deviation of percentage shares of value-added from abroad for the different industries was only 0.3% from 2009 to 2016. This suggests that the breakdown of value added from abroad across different industries does not vary much over time. Similarly, the BEA's data on value added from foreign direct investment (FDI) in the US broken down by industry (BEA, 2018e) was used to disaggregate F4, but was only available from 2007 onwards. F4 in the 2003 SAM was thus disaggregated using 2007 proportions. Once again, this was a reasonable approximation, as the average standard deviation of percentage shares of value-added from FDI for the different industries was only 0.5% from 2007 to 2016. There also wasn't a 2003 edition of the Federal Reserve's Survey of Consumer Finances (SCF) (Fed, 2018), so Hcur2 in the 2003 micro-SAM was disaggregated using the 2004 SCF. Finally, there has only been one nationwide survey of household money sent to and received from abroad that covered both native and foreign-born households – the 2008 Current Population Survey (CPS) immigration/emigration supplement (Census, 2018a). As such, Hcur5 and R3 in all micro-SAMs were disaggregated in the proportions indicated in 2008[85].

Sometimes, surveys used slightly different industry classifications than the SAMs. For example, while

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[85] 2008 household income quintile income limits from Census Bureau's historical income tables (Census, 2018b) were used to determine the proportional split between the household income groups.

both the SAM and the CPS (Census, 2018a) use the North American Industry Classification System (NAICS), they use different levels of aggregation, so a few of the SAM industries span more than one CPS category. In such cases, the wages paid in the CPS by each industry to each household income quintile were added together before the proportional split between income quintiles was estimated for the given SAM industry. This thus took account of the relative employee numbers and wage levels in the different CPS industries in the SAM category. Similarly, when looking at FDI in the US and US direct investment abroad for F4 and R2 respectively, where a BEA NIACS category spanned more than one SAM NIACS categories, the former's value-added to or from abroad was distributed across the relevant SAM categories in proportion to each SAM categories' domestic value added. This assumed that US companies operating abroad in a given industry have similarly specialisms to all other US companies operating in that industry, and that foreign companies operating in a given industry in the US are similarly focused to domestic companies operating in that industry.

Finally, it was necessary to interpolate between data for different household income groups in the CPS to allocate wages to household income quintiles. In F1, for example, to estimate the percentage breakdown of labour payments from each sector to each household income quintile, data on average weekly earnings paid by each industry to employees in 15 different average weekly earnings 'bins'[86] were used in combination with data on the number of employees in that industry in each average weekly earnings bin, broken-down across the 16 CPS annual household income bins to which those respondents belonged. The CPS annual household income bins, however, generally did not correspond to household income quintile limits estimated by the United States Census Bureau (Census, 2018b). In such cases, linear interpolation was used to estimate how many employees in the income bin in question fell above and below the relevant quintile income limit.

While economists sometimes approach such problems by fitting parametric distributions, curve fitting is time and computationally intensive, as different distributions must be tried and compared. Creating the three micro-SAMs would require fitting 2,340 curves, even without trying different distributions, so this approach was not feasible. Distribution fitting can also result in a curve that produces large errors for individual bin counts (von Hippel et al., 2017). An alternative popular method is to assume that everyone in a household income bin earns the income at the bin mid-point; however, as the F1 submatrix is a crucial part of the micro-SAM for understanding inequality dynamics, this method was deemed too crude. Given that the results of subsequent IOA were not being viewed as precise predictions, only approximate estimates to help reveal possible tendencies and channels of impact, interpolation was deemed an appropriate compromise between the two

[86] An example of an earnings bin is an employee earning between 400.01 USD and 600 USD per week.

approaches. Linear interpolation was chosen over cubic-splines because, when estimating Gini coefficients from binned income data for each of the 3,221 US counties, linear and cubic-spline interpolations were found to produce very similar results (von Hippel et al., 2017). Linear interpolation is also used by US national statistics bodies, such as the U.S. Census Bureau, to estimate population density within an income interval (FED, 2018c).

All CPS data had to be weighted so that survey results would reflect characteristics for the entire US population. The weights coded 'HWHHWGT' were used, as the U.S. Census Bureau recommends these for studies focused on household characteristics.

As discussed, the SAMs were balanced using the statistical discrepancy account as a residual, with the account total corresponding to the statistical discrepancy in the NIPAs. Prior to balancing, the 2003, 2010 and 2016 micro-SAM account totals deviated from their target values, on average, by 0.6%, 0.8% and 1.1% respectively.

### 4.3.3 US edu-SAM

In addition to having disaggregated household accounts, to meaningfully explore drivers of inequality a SAM must also have sufficiently disaggregated factor accounts. If the labour account, say, is not disaggregated, then household groups will receive a fixed percentage of any new wages, regardless of which industry has generated these wages. This is a very incomplete picture of the drivers of inequality in an economy (Pieters, 2010). Pieters (2010), in addition, proposed that labour accounts disaggregated by industry, not just labour accounts disaggregated by, say, level of education, are required to observe differing inequality effects from growth in different sectors. An alternatively disaggregated 2016 US micro-SAM was thus created to test this conjecture. This thesis was, consequently, able to make a further methodological contribution to IOA, in terms of the information and model set-up required to enable proper exploration of inequality questions. This analysis can be found in Chapter 8.

The alternative 2016 SAM, hereafter called the 'edu-SAM', was identical to the 2016 micro-SAM, except that value added was disaggregated into seven value added accounts, five of which were labour accounts broken down by educational attainment[87], instead of 71 industry value added accounts. The educational categories that feature in the CPS were used. Appendix F lists these alternative accounts, while Appendix D lists the data used for each alternatively disaggregated element.

When using CPS data for I2, the same weekly earnings bin approach was taken as with the other

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[87] The other two value added accounts were capital and indirect taxes less subsidies.

micro-SAMs. Instead of looking at the spread of employees in each industry in each earning bin across each household income group, the distribution of employees in each industry in each earning bin across each educational category was used in combination with earnings paid by each industry to each earnings bin.

F1 was first disaggregated across educational categories in proportion to CPS data on total earnings across all industries broken down by employees' level of education. It was then further disaggregated using data on the number of employees in each education groups across the different household income quintiles. Linear interpolation across CPS household income bins was once again used.

Finally, F4 and R2 were disaggregated into labour, capital and indirect taxes less subsidies using the usual BEA data on FDI in the US and US direct investment abroad respectively. Data on indirect taxes less subsidies was not directly available, but could be calculated as its equal to total value added less compensation of employees and net income. The labour components of F4 and R2 were then disaggregated using CPS data on total earnings across the different educational categories. This assumed that US companies operating abroad and foreign companies operating in the US employ similarly educated workers to US companies operating domestically.

Prior to balancing, the edu-SAM account totals deviated from their target values by 0.9% on average.

## 4.4 Adapting other SAMs

### 4.4.1 Alaska

The 2008 Alaskan SAM (Seung, 2014) is disaggregated into 35 commodities, 35 industries, 3 Alaskan household income groups[88], but only one labour account. As discussed, in addition to having disaggregated household accounts, to meaningfully explore drivers of inequality a SAM must also have sufficiently disaggregated factor accounts. The Alaskan labour account thus needed to be disaggregated into industry labour accounts so that fuller inequality effects could be observed.

Like the transition from US macro-SAMs to micro-SAMs, data from surveys was used only to indicate the proportions by which elements in the original SAM were disaggregated; the total value of aggregates remained unchanged to preserve the information contained in the peer-reviewed Alaskan SAM.

[88] The three household income groups are annual incomes of (i) less than USD 25,000, (ii) USD 25,000 to 75,000, and (iii) greater than USD 75,000.

In the original Alaskan SAM, the labour account receives 99.8% of its income from Alaskan industries, and only 0.2% of its income from savings-investment account. The latter was a residual payment to balance the labour account. As such, the labour account total was disaggregated into industry labour account totals in proportion to the labour payments made by each Alaskan industry. As the income from the savings-investment account was already a residual, it was disaggregated in the proportions required to balance the industry labour accounts.

On the payments side of the Alaskan labour account, there were flows to the state and local government and federal government accounts. These payments do not represent direct or indirect taxes, as these are paid elsewhere in the SAM, so they were assumed to be transfers from the Alaskan state and local government and federal government labour accounts respectively to the state and local government and federal government current accounts. The wages paid out by the Alaskan state and local government and federal government labour accounts could then be estimated as the residual of the account totals minus the aforementioned transfers to the state and local government and federal government current accounts. These wages, and the account totals for all other Alaskan labour accounts[89], then needed to be split between wages paid to Alaskan households and wages paid to the rest of the US[90].

The Alaskan Department of Labor and Workforce Development publishes data estimating total wages paid to residents and non-residents by industry (DOLWD, 2010). The proportions indicated for each industry were thus used to disaggregate the wages paid by each industry between Alaskan households and the rest of the US. DOLWD (2010) does not collect data on the fish-harvesting industry, so it was assumed that the agricultural and fish-harvesting labour accounts paid the same proportion of total wages to out-of-state workers. Similarly, DOLWD (2010) also does not collect data on federal government wage payments in Alaska, so it was assumed that the Alaskan state and local government and Alaskan federal government labour accounts paid the same proportion of total wages to out-of-state workers

Having estimated the breakdown of labour payments by each industry to Alaskan households, these were allocated to the different household income groups using CPS data, as the latter could be extracted at the state-level. The same process was followed as with the US micro-SAMs. Out of the 35 industries, there were five, agriculture, food manufacturing, other manufacturing[91], wholesale

[89] All other Alaskan labour accounts make only two payments; the first to Alaskan households and the second to the rest of the US.
[90] Seasonal non-resident workers make up approximately 20% of Alaska's workforce (DOLWD, 2010).
[91] Other manufacturing includes all manufacturing except food and petroleum and coal products manufacturing.

trade, and management of companies and enterprises, for which no Alaskan CPS data was available. For these industries, the distribution of wages across the three household groups was determined using the distribution indicated by US, not Alaska-specific, data. As other manufacturing contained 13 different NIACS manufacturing codes, to estimate the overall distribution, the distributions indicated for each code were weighted by the relative compensation of employees in Alaska in 2008 for each relevant industry, which were obtained from the BEA (BEA, 2018f). One of the industrial categories in the Alaska SAM, 'miscellaneous', could not be associated with any NIACS industry code. So the overall CPS distribution of wages across the three household groups from Alaskan industries collectively was used for this category.

The RAS procedure was then used across these disaggregated labour account payments to reconcile the survey data with the submatrix totals in the original peer-reviewed SAM.

### 4.4.2 Adjustments to other SAMs

Slight adjustments were made to all the other SAMs. Firstly, as FUND estimates changes to total agricultural production and does not break this down by product, all agricultural activities and commodities in the original SAMs needed to be aggregated into one agriculture activity and one agriculture commodity account. Secondly, all the original SAMs had disaggregated households in varying ways; for example, broken down by location, i.e. the region or rural or urban, by the gender of the head of household, or by the tribal group. In the original SAMs, within these groups, households were then further broken-down into national income or expenditure quintiles or deciles. To enable comparisons across SAMs, households were aggregated into income or expenditure quintiles, with all further divisions removed. Finally, as all FUND damage and income growth estimates are in 1995 USD billions, all SAMs were converted into 1995 USD billions.

Micro-SAMs for all seven countries and Alaska are available from the author upon request[92], and a list of all accounts in each micro-SAM is provided in Appendix F.

## 4.5 Summary

This chapter introduced SAMs and explained how they are constructed; in particular, how algorithmic and residual techniques are used to balance the SAM to ensure that all spending and saving is financed. In this thesis, residual accounts were used to balance SAMs to ensure that national accounts data was preserved. It also meant that survey data used to disaggregate submatrices in SAMs would not be arbitrarily adjusted. Residual accounts will be assumed to be

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exogenous to the model in the IOA in chapters 6 and 7, so they will not influence results. Where using two different surveys to disaggregate a SAM element or using the same survey in different ways would produce different results, the RAS procedure was used to reconcile the different survey results by adjusting the less confidently known disaggregated sub-matrix elements to the more confidently known submatrix row and column totals. Such reconciliation procedures are common in SAM construction.

This chapter then detailed the data sources used to compile the US SAMs and how the data was used. As data time-series were available, a time-series of US SAMs, for 2003, 2010 and 2016, was compiled to empirically explore the extent that useful lessons for a country's future can be learnt from an IOA of a recent SAM. This analysis can be found in Chapter 5. As compiling SAMs is highly time and data intensive, very few SAM time series currently exist. Constructing such a time-series was, thus, a useful extension, and a methodological contribution to IOA. Such empirical tests could hitherto only be found for IOT, not SAM, time-series. The analysis was also used to guide which accounts were assumed to be exogenous to the model in the IOA in Chapters 6 and 7.

This chapter then went on to compile an alternatively disaggregated US 2016 micro-SAM to test the result in Pieters (2010) that labour accounts disaggregated by industry, not just labour accounts disaggregated by level of education, are required to observe differing inequality effects from growth in different sectors. This thesis was, thus, able to make a further methodological contribution to IOA, in terms of the information and model set-up required to enable proper exploration of inequality questions. This analysis can be found in Chapter 8.

Finally, this chapter then detailed how the labour account in the Alaskan SAM that was needed for the impact studies case study in Chapter 7 was disaggregated so that fuller inequality effects could be observed. The small adjustments made to the SAMs for the other countries that feature in the IAM case study in Chapter 6 were also explained.

# Chapter 5 – Coupling methodology

This chapter introduces input-output analysis (IOA), the strengths and weaknesses of demand-side and supply-side models, the plausibility of assumptions, and equivalence of the models under a specific interpretation. This analysis suggests that the Leontief quantity model is most appropriate for this thesis, with the mixed endogenous-exogenous (MEE) version used to incorporate supply constraints where necessary. The chapter then details the coupling methodology used in the case studies to estimate income inequality effects from climate impacts. Approaches for different types of impacts are provided. Finally, the chapter analyses social accounting matrix (SAM) time-series to explore if useful lessons for the future of a country might be learnt from its recent SAM, or if, instead of concentrating on a country's specific results, general lessons should be drawn from across a range of countries.

## 5.1 Introduction to input-output analysis

Having established in Chapter 3 that IOA is the most appropriate tool to bring economic inequality into couple economic-environmental models and thus answer the research questions outlined in Chapter 2, let us now explore the theory underpinning IOA, and the different ways it can be applied.

### 5.1.1 The Leontief model

The macroeconomy can be affected by demand or supply-side events. In a demand-side shock, for example, consumer demand for specific goods falls, resulting in these industries having fewer orders to fulfil, and so they themselves need fewer intermediate goods, i.e. goods used in production processes. This translates into changed demand for other industries, so the initial demand shock has a multiplier effect across the economy, which can be modelled using *Wassily* Leontief's input-output quantity model (Leontief, 1936).

The latter starts with a social accounting matrix (SAM), where some of the accounts are deemed exogenous[93] to the model, while the remaining endogenous accounts are taken to form a matrix of inter-and intra-account transactions, $\boldsymbol{Z}$. One then defines a matrix of 'technical coefficients', $\boldsymbol{A}$ , with elements $a_{ij}$ describing the monetary payment[94] by account $j$ to account $i$, per unit of account $j$'s total expenditure, such that $\boldsymbol{A} = \boldsymbol{Z}\widehat{\boldsymbol{x}}^{-1}$, where $\boldsymbol{x}$ is a vector of the total expenditures of each endogenous account, $\widehat{\boldsymbol{x}}$ is a diagonal matrix with the elements of $\boldsymbol{x}$ forming its main diagonal, and

[93] Exogenous variables are inputs into the model, but they are not themselves affected by relationships specified in the model. Endogenous variables, in contrast, are determined by the model.
[94] $\boldsymbol{Z}$ typically captures monetary flows; although physical flows are sometimes used.

$\hat{\boldsymbol{x}}^{-1}$ is its inverse. As the SAM is balanced, total expenditure is equal to total income for every account, so $\boldsymbol{x}$ can also be interpreted as a vector of the total incomes of each endogenous account. If $\boldsymbol{f}$ is a vector of the aggregate monetary flows from all exogenous accounts to each endogenous account then, by definition[95], $\boldsymbol{x} = \boldsymbol{Zi} + \boldsymbol{f}$, and so $\boldsymbol{x} = \boldsymbol{Ax} + \boldsymbol{f}$, where $\boldsymbol{i}$ is a vector of ones of length $m$, and $m$ is the length of $\boldsymbol{Z}$. This can be rearranged to give $\boldsymbol{x} = \boldsymbol{Lf}$, and, if the technical coefficients remain constant, one can take derivatives to get

$$d\boldsymbol{x} = \boldsymbol{L}d\boldsymbol{f} \qquad (5.1)$$

where $\boldsymbol{L}$ is the 'Leontief inverse matrix', $\boldsymbol{L} = (\boldsymbol{I} - \boldsymbol{A})^{-1}$, and $\boldsymbol{I}$ is the identity matrix. If the determinant of $\boldsymbol{I} - \boldsymbol{A}$ is nonzero, which will be true for any typical economy[96], then this system of linear equations has a unique solution. As can be seen from $\boldsymbol{L}$'s Taylor series, the elements of the Leontief inverse reflect the infinite round-by-round effects of the direct change in exogenous spending, plus the indirect effects of the latter on all sectors, and the subsequent indirect effects of those changes on all sectors, and so on[97]. Changes in exogenous demand thus instigate changes in total output.

This is a linear model that assumes Leontief production functions. These are fixed production recipes, so no substitution can occur between intermediate goods or factors of production, and it is assumed there is no technological change. As the technical coefficients in $\boldsymbol{A}$ remain constant, this implies that economies of scale have been realised, and no diseconomies of scale have been triggered. A monetary flow from sector $j$ to sector $i$, $Z_{ij}$, is equivalent to the price of the good or service supplied by $i$, $P_i$, multiplied by the quantity of the good or service that sector $j$ has bought, $Q_{ij}$. The Leontief quantity model assumes that prices are constant, and $\Delta\boldsymbol{f}$ and $\Delta\boldsymbol{x}$ both represent quantity changes[98].

Constant prices require perfectly elastic supply. This means a horizontal supply curve, where any decrease in price would cause supply to collapse. It also means that an infinite supply of the good could theoretically be provided at the current price, i.e. there are no shortages or other constraints

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[95] Leontief's model was developed for input-output tables (IOTs), where this national accounting identity is interpreted as total output is equal to intermediate demand plus final demand. The latter means institutional demand, i.e. demand from households, government and the rest-of-the-world (ROW).
[96] For the determinant to be zero, there would need to be linear dependence between rows or columns of $\boldsymbol{L}$. This is highly unlikely due to the identity matrix, which is linearly independent. In addition, in a typical economy, the elements of $\boldsymbol{A}$ are less than one, as economic sectors and institutions interact with one another. For the determinant of $\boldsymbol{L}$ to be zero, at least one sector or institution would have to be completely isolated, so that the only nonzero technical coefficient for that sector would be a 1 on the leading diagonal, and even this could be avoided by disaggregating the account.
[97] The Taylor series is presented in Miller and Blair (2009), along with an explanation.
[98] Leontief also presented an alternative IO model where prices change while quantities remain constant.

on production. In reality, no goods or services have perfectly elastic supply, so, as stated in Chapter 3, the assumptions underlying input-output analysis (IOA) are imperfect approximations.

### 5.1.2 The Ghosh model

Supply-side effects stem from changes in the availability of goods or services that are used in other production processes. Supply constraints in the oil and gas industry, for example, could reduce output in sectors that need these fuels in their own production processes. Reduced output in these affected industries, in turn, can then affect production in yet more sectors, and so on. Ambica Ghosh proposed an alternative input-output framework to model these multiplier effects (Ghosh, 1958).

Leontief's matrix of technical coefficients, $\boldsymbol{A}$, divided the elements in each column of $\boldsymbol{Z}$ by their respective column totals. This shows how an account's total expenditure is distributed across different sectors and institutions. Ghosh's innovation was to instead divide elements of $\boldsymbol{Z}$ by their row total, and thus explore the distribution of sources of income for each account. A new square matrix, $\boldsymbol{B} = \hat{\boldsymbol{x}}^{-1}\boldsymbol{Z}$, was defined and called the matrix of 'allocation coefficients', where elements $b_{ij}$ describe the percentage of sector $i$'s income that stems from sector $j$. If $\boldsymbol{v}$ is a vector of the aggregate monetary flows from each endogenous account to all exogenous accounts then, by definition, $\boldsymbol{x}^T = \boldsymbol{i}^T\boldsymbol{Z} + \boldsymbol{v}^T = \boldsymbol{x}^T\boldsymbol{B} + \boldsymbol{v}^T$, where the $T$ superscript indicates transposition. If allocation coefficients remain constant, then one can differentiate to get $d\boldsymbol{x}^T = (d\boldsymbol{v}^T)\boldsymbol{G}$, where $\boldsymbol{G} = (\boldsymbol{I} - \boldsymbol{B})^{-1}$, and is called the 'output inverse matrix'.

If at least one factor of production, i.e. land, labour or capital, is assumed exogenous, then this model can be used to estimate how changes in the availability of primary inputs can drive changes in total output[99]. Once again, prices are assumed to be fixed, so fixed allocation coefficients imply perfectly elastic demand, i.e. at the given price any additional output will be purchased. This is, of course, an imperfect approximation of real economic behaviour. Fixed allocation coefficients are more controversial than fixed technical coefficients, as they cannot be explained by microeconomic theory. In contrast, fixed technical coefficients are consistent with firms minimising costs under perfect competition and fixed prices, assuming no technological innovation (Oosterhaven, 1989).

Ghosh developed his model for "a monopolistic market with scarce resources", and cautioned that "allocation functions will play a minor role" when these conditions are not met (Ghosh, 1958). He argued that "our discussion is confined to a consideration of economies with a high rate of investment, with inadequacy of the supply of productive plants and materials and with a rationing system in allocation." Ghosh argued, for example, that planned economies have social goals, and

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[99] The Ghosh model was developed for IOTs, where $\boldsymbol{v}$ captures only value added.

firms are instructed to distribute their products to help realise these targets, even though this may mean not minimising costs and maximising profits. Ghosh also noted that in times of extreme scarcity, market economies can become at least partially planned; for example, the government may ration food, as the British government did during World War II. Ghosh thus thought that technical coefficients would be more stable under some circumstances and allocation coefficients more stable under others. Economists have mostly applied Ghosh's model to market economies in times of shortages. Giarratani (1981) justifies this by arguing that when businesses are forced to ration output they distribute amongst clients in proportion to the latter's former purchases to avoid losing customers.

A further problem with the Ghosh model is that, when applied to input-output tables (IOTs), it assumes that output in sectors that are not subject to the exogenous change in primary inputs[100] can be increased without additional capital, land or labour. This is implausible, except in the unusual situation where factor inputs in these industries are originally underutilised (Oosterhaven, 1988). When such hoarding does not take place, the Ghosh model implies that intermediate goods can be substituted for factor inputs in production.

A final concern surrounding the Ghosh model is that, as $\boldsymbol{A} = \boldsymbol{Z}\widehat{\boldsymbol{x}}^{-1}$ and $\boldsymbol{B} = \widehat{\boldsymbol{x}}^{-1}\boldsymbol{Z}$, $\boldsymbol{A} = \widehat{\boldsymbol{x}}\boldsymbol{B}\widehat{\boldsymbol{x}}^{-1}$. To see why this is problematic, consider two years, $t_1$ and $t_2$, and let the superscripts $t_1$ and $t_2$, indicate the values of variables in those years. $\boldsymbol{A}^{t_2} = \widehat{\boldsymbol{x}}^{t_2}\boldsymbol{B}^{t_2}(\widehat{\boldsymbol{x}}^{t_2})^{-1}$. If $\boldsymbol{B}$ is constant, however, then $\boldsymbol{B}^{t_1} = \boldsymbol{B}^{t_2}$, and so $\boldsymbol{A}^{t_2} = \widehat{\boldsymbol{x}}^{t_2}\boldsymbol{B}^{t_1}(\widehat{\boldsymbol{x}}^{t_2})^{-1} = \widehat{\boldsymbol{x}}^{t_2}(\widehat{\boldsymbol{x}}^{t_1})^{-1}\boldsymbol{A}^{t_1}\widehat{\boldsymbol{x}}^{t_1}(\widehat{\boldsymbol{x}}^{t_2})^{-1}$. It is therefore impossible for both $\boldsymbol{A}$ and $\boldsymbol{B}$ to remain constant given changes in output, unless the output of all sectors increases by the same proportion, $r$, so that $\boldsymbol{A}^{t_2} = (r\boldsymbol{I})\boldsymbol{A}^{t_1}\left[\left(\frac{1}{r}\right)\boldsymbol{I}\right] = \boldsymbol{A}^{t_1}$. When this condition is not fulfilled, the key assumptions underpinning the Ghosh and Leontief models cannot simultaneously be correct.

The Ghosh model thus assumes that all inputs can be substituted for one another in production processes. Gruver (1989) argued that such substitution is not arbitrary as it reflects the linearization of production functions in input-output economics. Oosterhaven (1989) countered that this will only be true under strict conditions, and that the Ghosh model does not allow output to increase in sectors whose products are substitutes for a constrained good. Many economists thus believe that technical coefficients adjustment in the Ghosh model is not consistent with the realities of production.

Studies have empirically explored the extent that technical coefficients change when the Ghosh model is applied. Chen and Rose (1986), for example, modelled a supply-shock using an input-output

[100] 'Primary inputs' is a synonym for factors of production.

table for Taiwan, and observed that technical coefficients in the account subject to exogenous effects changed by more than five per cent; although technical coefficients in other accounts changed by less than this, and only three per cent of all coefficients were altered by more than one per cent. Rose and Allison (1989) similarly applied the Ghosh model on an IOT for Washington State and found that no technical coefficient changed by more than four per cent. Such studies thus indicate that while joint-stability issues are not negligible, most coefficients do not experience large changes. Rose and Allison (1989) further noted that the effects of coefficient changes are often more limited than those introduced by algorithmic matrix-updating techniques that are widely used in the IOA literature[101].

In addition, studies have taken time-series of IOTs to explore how allocation and technical coefficients vary over time. Giarratani (1981), for example, looked at United States (US) IOTs for 1963 and 1967, and found that coefficients in the Leontief model did not, on average, appear to be more stable than their Ghoshian counterparts. In a United Kingdom (UK) study, Bon (1986) used 1947 IOT technical and allocation matrices, combined with value added and final demand data for five years between 1958 and 1977, to project total output in those years using both Leontief and Ghoshian models. When comparing these forecasts to realised output data, he found that, while the Leontief model slightly outperformed the Ghosh for total output projections, one could not definitively support one model over the other, as the supply-side model performed better for certain sectors. Augustinovics (1970) compared changes in technical and allocation coefficients in Hungarian IOTs spanning from 1959 to 1964, and agreed that one cannot conclusively support one model over the other. Oosterhaven (1988) and De Mesnard (2009) also noted that empirical analyses are inconclusive.

The aforementioned theoretical issues, however, led most economists to reject the Ghosh model until Dietzenbacher (1997) reinterpreted the model as a price model. Instead of taking prices as constants and allowing quantities to vary, which was how the Ghosh model was typically deployed, Dietzenbacher proposed that prices should instead be allowed to vary while quantities are held constant. In other words, as an industry's factor inputs become more expensive, they will pass these costs on to the businesses and consumers who buy their products. Viewing the Ghosh model as a price model means that one does not need to worry about outputs increasing without a corresponding increase in primary inputs, as no quantities change. The coefficient joint-stability

[101] In addition to balancing matrices, the algorithmic processes described in Chapter 4 are often used to estimate a recent IOT or SAM from an older matrix using only a subset of the otherwise-required up-to-date information (Miller and Blair, 2009).

issues also are no longer a concern, as they now represent price adjustments, rather than substitution.

Dietzenbacher (1997) further demonstrated that the Ghosh price model is equivalent to the price version of Leontief's quantity model. Moreover, he proposed an alternative quantity model derived from allocation coefficients that gave the same results as Leontief's quantity model. In short, regardless of whether technical or allocation coefficients are used, one has a single demand-pull quantity model and a single cost-push price model. The given research question will indicate which model should be utilised. Finally, Dietzenbacher (1997) observed that the Leontief and Ghosh models are the most computationally efficient expressions of the quantity and price models respectively.

Note, however, that as the Ghosh price model assumes fixed quantities, it cannot be used to explore supply constraints. So how can the effects of limited resources be explored in an IO framework?

### 5.1.3 The mixed-endogenous-exogenous (MEE) model

As the Ghosh model is generally not considered to be a valid supply-driven model, a 'mixed-endogenous-exogenous' (MEE) model was introduced. This approach adapted the Leontief quantity model so that total income is exogenous for some accounts, instead of demand.

If $\boldsymbol{A}$ is arranged so that the $n$ row and column accounts with endogenous account totals are at the top and left respectively, with the remaining $m-n$ accounts with exogenous account totals at the bottom and right respectively, then one can write Leontief's accounting identity as

$$\left(\begin{bmatrix} \boldsymbol{I} & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{I} \end{bmatrix} - \begin{bmatrix} \boldsymbol{A_{11}} & \boldsymbol{A_{12}} \\ \boldsymbol{A_{21}} & \boldsymbol{A_{22}} \end{bmatrix}\right)\begin{pmatrix} \boldsymbol{x}^{(en)} \\ \boldsymbol{x}^{(ex)} \end{pmatrix} = \begin{pmatrix} \boldsymbol{f}^{(ex)} \\ \boldsymbol{f}^{(en)} \end{pmatrix}$$

where $\boldsymbol{A_{11}}$, $\boldsymbol{A_{12}}$, $\boldsymbol{A_{21}}$ and $\boldsymbol{A_{22}}$ are matrices containing the technical coefficients in rows $1$ to $n$, $1$ to $n$, $n+1$ to $m$, and $n+1$ to $m$ respectively, and columns $1$ to $n$, $n+1$ to $m$, $1$ to $n$, and $n+1$ to $m$ respectively of $\boldsymbol{A}$. $\boldsymbol{I}$ and $\boldsymbol{0}$ are appropriately sized identity and null matrices respectively. $\boldsymbol{x}^{(en)}$, $\boldsymbol{x}^{(ex)}$, $\boldsymbol{f}^{(ex)}$ and $\boldsymbol{f}^{(en)}$ are vectors of endogenous account totals, exogenous account totals, exogenous final demand and endogenous final demand respectively. By multiplying out these equations, one gets

$$(\boldsymbol{I} - \boldsymbol{A_{11}})\boldsymbol{x}^{(en)} - \boldsymbol{A_{12}}\boldsymbol{x}^{(ex)} = \boldsymbol{f}^{(ex)} \qquad (5.2)$$

and

$$(\boldsymbol{I} - \boldsymbol{A_{22}})\boldsymbol{x}^{(ex)} - \boldsymbol{A_{21}}\boldsymbol{x}^{(en)} = \boldsymbol{f}^{(en)} \qquad (5.3)$$

These can then be rearranged so that all exogenous vectors are on the right hand side, which gives

$$\begin{bmatrix} (\boldsymbol{I}-\boldsymbol{A_{11}}) & \boldsymbol{0} \\ -\boldsymbol{A_{21}} & -\boldsymbol{I} \end{bmatrix} \begin{pmatrix} \boldsymbol{x}^{(en)} \\ \boldsymbol{f}^{(en)} \end{pmatrix} = \begin{bmatrix} \boldsymbol{I} & \boldsymbol{A_{12}} \\ \boldsymbol{0} & (\boldsymbol{A_{22}}-\boldsymbol{I}) \end{bmatrix} \begin{pmatrix} \boldsymbol{f}^{(ex)} \\ \boldsymbol{x}^{(ex)} \end{pmatrix}$$

or

$$\begin{pmatrix} \boldsymbol{x}^{(en)} \\ \boldsymbol{f}^{(en)} \end{pmatrix} = \boldsymbol{M}^{-1}\boldsymbol{N} \begin{pmatrix} \boldsymbol{f}^{(ex)} \\ \boldsymbol{x}^{(ex)} \end{pmatrix} \qquad (5.4)$$

where $\boldsymbol{M} = \begin{bmatrix} (\boldsymbol{I}-\boldsymbol{A_{11}}) & \boldsymbol{0} \\ -\boldsymbol{A_{21}} & -\boldsymbol{I} \end{bmatrix}$ and $\boldsymbol{N} = \begin{bmatrix} \boldsymbol{I} & \boldsymbol{A_{12}} \\ \boldsymbol{0} & (\boldsymbol{A_{22}}-\boldsymbol{I}) \end{bmatrix}$. This system of linear equations will have a unique solution provided $\boldsymbol{M}$ is not 'singular', i.e. the determinant of $\boldsymbol{M}$, det $(\boldsymbol{M})$, is non-zero.

The determinant of a partitioned matrix $\begin{pmatrix} \boldsymbol{C} & \boldsymbol{D} \\ \boldsymbol{E} & \boldsymbol{F} \end{pmatrix}$ is equal to $det(\boldsymbol{C}-\boldsymbol{D}\boldsymbol{F}^{-1}\boldsymbol{E}) \times det(\boldsymbol{F})$ if $\boldsymbol{F}$ is not singular, or $det(\boldsymbol{C}) \times det(\boldsymbol{F}-\boldsymbol{E}\boldsymbol{C}^{-1}\boldsymbol{D})$ if $\boldsymbol{C}$ is not singular (Powell, 2011). Since the negative identity matrix is invertible, det $(\boldsymbol{M}) = det(\boldsymbol{I}-\boldsymbol{A_{11}})det(-\boldsymbol{I}) = (-1)^{m-n}det(\boldsymbol{I}-\boldsymbol{A_{11}})$. $\boldsymbol{M}$ will thus only be singular if $det(\boldsymbol{I}-\boldsymbol{A_{11}}) = 0$, which, as discussed earlier, is highly unlikely in an economy. The system of equations should, therefore, have a unique solution.

(5.2) can be rearranged to give $\boldsymbol{x}^{(en)} = (\boldsymbol{I}-\boldsymbol{A_{11}})^{-1}[\boldsymbol{f}^{(ex)} + \boldsymbol{A_{12}}\boldsymbol{x}^{(ex)}]$. As this equation involves only $\boldsymbol{A_{11}}$ and $\boldsymbol{A_{12}}$, it shows that endogenously determined account totals are affected solely by the indirect effects stemming from accounts with endogenous and exogenous totals buying from accounts with endogenous totals. Indirect effects from accounts with endogenous and exogenous totals buying from accounts with exogenous totals are not included, which means that interactions between accounts with exogenous totals are ignored. This contrasts with the Leontief model, where totals are dependent on all indirect effects between sectors.

Similarly, (5.3) can be rearranged to give $\boldsymbol{f}^{(en)} = (\boldsymbol{I}-\boldsymbol{A_{22}})\boldsymbol{x}^{(ex)} - \boldsymbol{A_{21}}\boldsymbol{x}^{(en)}$. This, along with (5.2), implies that $\boldsymbol{f}^{(en)} = (\boldsymbol{I}-\boldsymbol{A_{22}})\boldsymbol{x}^{(ex)} - \boldsymbol{A_{21}}(\boldsymbol{I}-\boldsymbol{A_{11}})^{-1}[\boldsymbol{f}^{(ex)} + \boldsymbol{A_{12}}\boldsymbol{x}^{(ex)}]$. As this expression involves $\boldsymbol{A_{11}}$, $\boldsymbol{A_{12}}$, $\boldsymbol{A_{21}}$ and $\boldsymbol{A_{22}}$, it demonstrates that endogenous final demand is determined by all indirect effects, whereas, in the Leontief model, it is exogenously specified and so independent of all indirect effects.

This MEE quantity model is commonly used to explore the indirect effects of supply constraints, particularly those stemming from natural resources. For example, see Eiser and Roberts (2002) and Leung and Pooley (2001). However, as discussed, it cannot estimate the impacts that constrained sectors may have on each other's total income – although this is to be expected, as the latter are exogenous.

### 5.1.4 Other input-output models of supply constraints

Instead of the MEE model, some input-output economists use a process called 'hypothetical extraction' to model supply constraints. This assumes that a sector can no longer operate, so all elements related to that industry in $\boldsymbol{A}$ and $\boldsymbol{f}$ are changed to zeros to create a new matrix of technical coefficients, $\boldsymbol{A}^*$, and vector of final demands, $\boldsymbol{f}^*$. The traditional Leontief model is then used to calculate new account totals, $\boldsymbol{x}^*$, via $\boldsymbol{x}^* = \boldsymbol{L}^*\boldsymbol{f}^*$, where $\boldsymbol{L}^* = (\boldsymbol{I} - \boldsymbol{A}^*)^{-1}$. $\boldsymbol{i}^T\boldsymbol{x} - \boldsymbol{i}^T\boldsymbol{x}^*$ is interpreted as the economic contribution of that sector to the economy; although, note that this methodology implicitly assumes that other sectors are able to use imports to replace the missing industry's product in their production processes.

Hypothetical extraction is traditionally used to estimate the importance of an industry to an economy, but it is sometimes adapted to model supply constraints by doing partial rather than full extraction (Dietzenbacher and Lahr, 2013). Partial extraction assumes that an industry has $\alpha$% reduced capacity. All row elements in $\boldsymbol{A}$ related to that industry are then assumed to reduce by $\alpha$% to reflect the reduced interindustry orders that industry can no longer fulfil. Note that the column elements of $\boldsymbol{A}$ related to that industry are not changed, as both the sector's total output and its intermediate purchases off other industries reduce by $\alpha$%, so these two reductions cancel out to leave the column technical coefficients unchanged.

There are also dynamic input-output based models, such as ARIO (Hallegatte, 2008) and the dynamic inoperability input-output model[102] (Barker and Santos, 2010), which model the recovery of an economy that is temporarily disrupted, for example, after a natural disaster. These typically also overcome some of the rigidity of traditional IO models by, for example, considering the role of imports or inventories in mitigating supply shocks, or allowing prices to change.

## 5.2 Coupling methodology

Having explored the mathematics and theory of IOA, and the different ways in which it has been adapted and applied, let us now consider how it can best be utilised to model the inequality effects of climate change impacts.

Climate change may bring physical changes that result in, say, increased or decreased agricultural production, available water resources, or electricity use for heating or cooling. These are quantity changes, and so quantity models, rather than price models such as the Ghosh price model, will be

[102] The static inoperability input-output model is a normalised version of Leontief's traditional model (Dietzenbacher and Miller, 2015).

used. While these quantity changes may result in price changes, the latter would be an effect, not the force driving change.

### 5.2.1 Final demand changes

Many climate change impact studies estimate final demand changes; for example, projected increased spending on coastal defence or energy for space cooling. Where this increased spending was by an exogenous account, such as government, the traditional Leontief model, i.e. equation (5.1), was easily applied.

Some damage studies, however, estimate increased spending by accounts that need to be endogenous if one is to estimate impacts on household inequality. For example, as interindustry purchases and households need to be endogenous, changes in energy *consumption* would require changing business activities' and household's technical coefficients. The latter cannot be accommodated in an input-output framework, so changes in energy expenditure were instead modelled as changes in *investment* in electricity. This could be implemented, because, as explained in Section 5.3.5 of this chapter, spending from capital-savings accounts formed part of final demand.

### 5.2.2 Output changes

Most other impact studies estimate changes to commodity production. In such cases, this thesis used the MEE quantity model, i.e. production was specified exogenously for the relevant commodity accounts, and impacts on other account incomes were estimated using equation (5.4).

The Ghosh quantity model has been widely discredited, so was not considered as a method for modelling output changes. Meanwhile, partial hypothetical extraction assumes that imports can compensate for the constrained industry's product in other industries' production processes. This was unrealistic for many of the industries that may be affected by climate change. For example, if domestic water resources are reduced, it seems unlikely that agricultural businesses will be able to import large quantities of water for use in irrigation, as large international trade of water for industrial purposes does not currently take place. Similarly, one cannot take for granted that food shortages in one country may be offset by agricultural production in another. It is plausible that climate change could increase global undernutrition (Wheeler and Von Braun, 2013). Similarly, global fisheries' revenues could decline (V. W. Lam et al., 2016). The MEE model assumes no changes to production recipes, so imports cannot mitigate supply constraints. Given the sectors being constrained by climate change, this assumption seemed most realistic.

Finally, sectors such as agriculture whose production may be impacted by climate change are most likely dealing with long-term changes in production, not once-off impacts. As such, the dynamic IOA based models that explore how an economy recovers after a natural disaster are not modelling the sort of impacts that feature this thesis[103].

### 5.2.3 Changes in economic surplus

Some partial equilibrium impact studies estimate impacts in terms of the change in 'economic surplus' or 'total welfare'. These terms, used interchangeably, refer to the sum of the 'consumer surplus' and the 'producer surplus'. The former is the amount that consumers have saved when paying the market price for a product versus the price that they would have been prepared to pay. The producer surplus, meanwhile, is the amount that producers have received by selling a product at the market price versus the price at which they would have been prepared to sell. The consumer surplus is the area below the demand curve and above the equilibrium price level, and a change in consumer surplus could be framed as a change in consumer savings. Meanwhile, the producer surplus is the area above the supply curve and below the equilibrium price level, and is often viewed as being approximately equal to profit.

Most partial equilibrium studies, while estimating the change in economic surplus, will also provide other economic measures of impact. For example, the partial equilibrium impact studies underlying the Climate Framework for Uncertainty, Negotiation and Distribution's (FUND's) forestry damage function estimate both the change in economic surplus and the change in forestry production. FUND's forestry damage function, however, only uses the economic surplus results, and so FUND's forestry damage estimates are expressed as a change in forestry consumer and producer surplus. Changes in consumer savings or producers profits are, of course, the end-point of an analysis into the economic effects of climate change on forestry. The force driving effects is the change in forestry yields. Consequently, results quoted purely in terms of changes to the economic surplus unfortunately cannot be used as inputs in an IOA of the inequality effects of climate change.

## 5.3 Empirically testing IOA assumptions

Having established the IOA coupling methodology that will be used in this thesis, let us now empirically explore the key limitation of IOA highlighted in Chapter 3, namely the linear nature of IOA and the resulting restrictive assumption of fixed production recipes. As discussed in Chapter 3, economies are nonlinear, and linear models are unable to capture the ways in which economies evolve and adapt over time. Chapter 3, however, argued that such disadvantages are, given this thesis' research questions, outweighed by IOA's advantages, particularly its simplicity, which means

[103] Note that the natural disaster impacts in Chapter 6 represent increased expenditure on reconstruction, not reduced production in impacted sectors.

that the mechanisms driving results are transparent and direct and indirect effects can easily be distinguished from one another. But how much can a simple linear model tell one about a complex nonlinear system? Can it capture enough of an economy's key attributes to contain useful information about what that economy might look like in the future, and, if so, over what approximate time period does this remain true?

While this thesis does not try to make precise predictions, it is still crucial to gauge the extent that lessons about the future can be learnt from an IOA of current SAMs. For example, this helps inform if analysing a country's results to get information for that specific country is implausible given the time-scales in questions, and if instead general lessons should be drawn from across a range of economies. It can also help guide which accounts are assumed exogenous as, if accounts that are highly variable do not feature in the internal mechanisms of the model, the model should remain realistic for longer.

### 5.3.1 Existing empirical tests of IOA

To the author's knowledge, there are no existing empirical tests of IOA using SAMs. This is most probably because creating a SAM is time and data-intensive, so very few SAM time-series currently exist. There are even fewer where all matrices have been produced by the same research team, and so use consistent methods, classification schemes and data-sources. IOT time-series are, however, commonplace, and studies have used these to empirically test IOA assumptions and predictions.

Bon (1986), for example, used the $\boldsymbol{L}$ and $\boldsymbol{G}$ matrices from UK IOTs from 1947, 1958, 1963, 1967, 1972 and 1977, along with final demand data for each of these years, to project sector and total output for future years. The total output estimates were found to be, on average, 5% and 7% away from the realised values, when using the Leontief and Ghosh models respectively. Meanwhile, the equivalent deviations for individual sector outputs were 17% and 10%, indicating that reliability increases with aggregation. The longest time-span covered in the study used the 1947 IOT to make projections for 1977. This produced total output estimates that were 6% and 11% away from the realised values, using the Leontief and Ghosh models respectively. At the sector level, the equivalent average deviations are 36% and 16%; however, much of this is down to one sector. Removing the latter brings the average deviations to 17% and 7%.

These predictions are far from perfect, particularly at the sector level, and suggest that *precise* predictions from IO models become implausible within decades. The projections, however, are reasonably close to the realised values, particularly given the thirty-year time horizon. This suggests that out-of-date models can still contain useful information. For example, some key attributes of the UK economy are retained between 1947 and 1977. Excluding the greatly altered sector, the relative importance of sectors to the UK economy was the same in both the predicted and realised data. Such continuity is of great value when conducting vulnerability analysis.

In a similar study, Dietzenbacher and Hoen (2006) used a 1948 – 1984 time-series of Dutch IOTs to empirically test how technical and allocation coefficients varied over the course of a year. Nearly four fifths of the coefficients were found to have a coefficient of variation[104] less than 0.3, which is generally considered low-variance. In addition, the larger coefficients, which have a greater impact on results, typically had lower coefficients of variation than their smaller counterparts.

The study also looked at how well an IOA using these IOTs could forecast outputs for a year later when (a) using the realised $\boldsymbol{f}$ vectors from later IOTs, i.e. perfect foresight scenarios, and (b) assuming the $\boldsymbol{f}$ vectors change by the same amount they did over the previous time period, i.e. scenarios without perfect foresight. The forecast root mean squared errors were, on average, 2.4% and 7.1% with and without perfect foresight respectively. This led Dietzenbacher and Hoen (2006) to conclude that it is more important to have realistic projections of exogenous changes than it is to project the evolution of technical or allocation coefficients.

Coefficients associated with flows from, say, households to enterprises or government may, however, not display the same degree of stability as those representing inter-industry consumption of good and services, and this could, in turn, change the predictive power of the model. Consequently, historic SAMs and IOTs could remain useful for different periods of time. This thesis will thus explore the reliability of SAM IOA predictions, along with the stability of SAM coefficients and other economic properties over time, to assess the extent that useful lessons for the future can be learnt from an IOA of recent SAMs.

### 5.3.2 Testing methodology

As discussed, SAM time-series are rare, which was the motivation behind creating one for the US in Chapter 4. Only three other series could be found where all matrices had been produced by the same research team, and so use consistent methods, classification schemes and data-sources. Only two of the series, those for Indonesia and Tanzania, had disaggregated factors and households. As this thesis is concerned with inequality dynamics, the time-series without the necessary disaggregation was dropped from the analysis. Indonesia and Tanzania do not feature in the case studies in Chapter 6 and 7, but one can still learn useful general lessons about the plausibility of IOA assumptions, and how SAMs vary with time, from studying non-case-study countries. While it would

[104] The coefficient of variation is the ratio of the standard deviation to the mean.

have been ideal to include case study regions, with the exception of the US, appropriate SAM time-series weren't available.

The time-series for Tanzania, Thurlow and Wobst (2015), allows one to compare SAMs three years apart, for 1998 and 2001, while the time series for Indonesia, BPS (2011), allows one to compare three pairs of SAMs ten years apart, 1975 and 1985, 1985 and 1995, and 1995 and 2005, two pairs of SAMs twenty years apart, 1975 and 1995, and 1985 and 2005, and one SAM pair thirty years apart, 1975 and 2005. The US time series constructed in Chapter 4 provides a pair of SAMs six years apart, 2010 and 2016, a pair of SAMs seven years apart, 2003 and 2010, and a pair of SAMs 13 years apart, 2003 and 2016. This thesis thus had short-term, medium term, and longer-term[105] SAM evolutions to study courtesy of Tanzania, the US and Indonesia, and Indonesia respectively.

Three analyses were performed. Firstly, the percentage change of technical coefficients in the SAMs over time was calculated to explore how well the key IOA assumption of fixed coefficients performs empirically. Secondly, following Bon (1986), Leontief inverse matrices derived from earlier SAMs were used, with realised exogenous demand data from later SAMs, to project output for those later years. Percentage errors between projected and realised output were then computed to examine forecasting power. Finally, 'backwards linkages', which are often used to estimate the relative interconnectedness of sectors and institutions, were analysed to assess whether the sectors relatively strongly and weakly connected with each household group changed over time.

The total backward linkage of a given sector is the change in the total income of all accounts produced by multiplier effects from a unit increase in exogenous money flowing into the given sector. A vector, $\boldsymbol{bl}$, containing the backwards linkages of each sector is thus given by $\boldsymbol{bl} = \boldsymbol{i}^T\boldsymbol{L}$. To normalise the measure, each linkage, $bl_j$, is often divided by the average linkage, $\sum_{j=1}^{n} bl_j/n$, where $n$ is the number of sectors. Sectors with normalised linkages greater (or less) than one are then interpreted as being relatively strongly (weakly) interconnected with other parts of the economy.

The sizes of the coefficients $l_{ij}$ in each column of $\boldsymbol{L}$ indicate what each sector $i$ receives from the multiplier effects of a unit increase in exogenous money flowing into $j$. This thesis is primarily interested in changes to household accounts, as these will be used to assess income inequality. Thus, rather than summing coefficients down each column of $\boldsymbol{L}$, for each household account, $h$, coefficients $l_{hj}$were normalised[106] to see if account $j$ was relatively strongly or weakly interconnected with that household group.

[105] Although 30 years, the longest time-lapse in this study, is short-term on a climate change time-scale.
[106] Only nonzeros were included when calculating average linkages for normalisation.

For this analysis, some accounts had to be assumed exogenous for each economy, or one would have infinite multiplier effects, reflected in $\boldsymbol{I}-\boldsymbol{A}$ being singular. For all countries, the rest-of-the-world (ROW) and capital accounts were assumed exogenous, as is common in IO literature. For the reasons outlined in Chapter 4, the statistical discrepancy account was also assumed exogenous for the US, and, following the coefficient stability analysis, as was the inventories account.

### 5.3.3 Testing fixed coefficients

Starting with the shortest time-span, the mean percentage change of nonzero Tanzanian technical coefficients between 1998 and 2001 was 12%. The mean percentage change of nonzero technical coefficients for each SAM account was 10%, with a standard deviation of 12%. Table 5.1 shows how this varied, on average, when these accounts were broken down into categories. Thus, even across a short four-year time horizon, one can see that coefficients aren't fixed. While the approximation seems very reasonable for value-added and government accounts, where coefficients vary, on average, by only 1%, coefficients in other accounts see more significant variation. Activities accounts, for example, saw the greatest variation, with coefficients changing, on average, by 14%, with a standard deviation of mean percentage changes of 17%.

Table 5.1 Mean percentage change of nonzero Tanzanian technical coefficients in each account, broken down by type of account

| **Type of account** | **Mean percentage change** | **Standard deviation of mean percentage change** |
|---|---|---|
| Commodities | 10% | 5% |
| Activities | 14% | 17% |
| Value-added | 1% | 1% |
| Households | 9% | 4% |
| Enterprises | 10% | 0% |
| Government and taxation | 1% | 3% |

Notes: Table shows the mean percentage changes of nonzero Tanzanian technical coefficients in each of the 121 Tanzanian SAM accounts between 1998 and 2001. The standard deviations of the mean percentage changes are also shown. Results are broken down by category of account, specifically into commodities, activities, value-added, households, enterprises, and government and taxation accounts. Results were derived from a Tanzanian SAM time series (Thurlow and Wobst, 2015).

Moving on to a medium time-horizon, the mean percentage changes of nonzero US technical coefficients between 2003 and 2010, 2010 and 2016, and 2003 and 2016 were 54%, 67% and 86% respectively. Table 5.2 shows how coefficients in each account performed, on average, when these accounts were broken down into categories. One can see that coefficients in the inventories account varied widely across all time periods, up to a maximum mean percentage change of 929% between 2003 and 2016. This suggests that the inventories account should be held exogenous in any multiplier analysis. Relatively large changes were also observed in the highly disaggregated commodities, activities and value-added accounts, with these accounts seeing maximum average mean percentage changes of 167%, 74% and 36% respectively. Between 2003 and 2010, the government account, which is not disaggregated, also saw large changes, with coefficients having a mean percentage change of 50%. This variance was likely down to policy changes and it supports the commonly held view that government spending patterns, like ROW spending patterns, frequently alter for reasons beyond the domestic economy. This is why government accounts are typically set exogenously in IOA. One can see from Table 5.2 that, in general, over the 13-year horizon, the assumption of fixed technical coefficients starts to look somewhat implausible. Although, the relatively poor performance of the seven and six-year US time periods versus the four-year Tanzanian example is likely down to a mixture of the longer time period and the US SAMs being more disaggregated[107]. As previously discussed, more disaggregated data is typically noisier.

Finally, moving on to Indonesia and longer time-steps, Table 5.3 shows the mean percentage changes of nonzero Indonesian technical coefficients between the different SAM years, while Table 5.4 shows how coefficients in each account performed on average, when these accounts were broken down into categories. One can see that changes are large across all account types in all time periods; in some cases, extremely large. Between 1985 and 2005, for example, the mean percentage change of nonzero technical coefficients was 4,989%. Once again, very large changes were at times observed in the government account, with the mean percentage changes of coefficients in this account being 21,388% and 19,265% between 1995 and 2005 and 1985 and 2005 respectively. Coefficients in activities accounts also sometime saw very large variation. Between 1985 and 2005, for example, the mean percentage change across activities accounts was 8,077%. The Indonesian SAM time-series thus suggests that even over the course of a decade, and particularly when going out twenty or thirty years, the assumptions of fixed technical coefficients become highly unrealistic.

[107] The US SAMs each have 222 accounts, whereas the Tanzanian SAMs each have 122.

Table 5.2 Mean percentage change of nonzero US technical coefficients in each account, broken down by type of account

| | 2003-2010 | | 2010-2016 | | 2003-2016 | |
|---|---|---|---|---|---|---|
| **Type of account** | **Mean percentage change** | **Standard deviation of mean percentage change** | **Mean percentage change** | **Standard deviation of mean percentage change** | **Mean percentage change** | **Standard deviation of mean percentage change** |
| Commodities | 69% | 121% | 160% | 451% | 167% | 635% |
| Activities | 50% | 34% | 43% | 43% | 74% | 105% |
| Value-added | 36% | 29% | 36% | 61% | 33% | 17% |
| Households | 22% | 3% | 24% | 8% | 23% | 2% |
| Enterprises | 19% | 0% | 89% | 0% | 22% | 0% |
| Government | 50% | 0% | 29% | 0% | 18% | 0% |
| Inventories | 516% | 0% | 284% | 0% | 929% | 0% |

Notes: Table shows the mean percentage changes of nonzero American technical coefficients in each of the 222 US SAM accounts across three time periods, 2003 to 2010, 2010 to 2016, and 2003 to 2016. The standard deviations of the mean percentage changes are also shown for each time period. Results are broken down by category of account, specifically into commodities, activities, value-added, households, enterprises, government, and inventories accounts. Results were derived from the US SAM time-series compiled in Chapter 4.

Table 5.3 Mean percentage change of nonzero Indonesian technical coefficients

| | **Mean percentage change of nonzero coefficients** |
|---|---|
| **10-year time step** | |
| 1975 - 1985 | 768% |
| 1985 - 1995 | 549% |
| 1995 - 2005 | 1379% |
| **20-year time step** | |
| 1975 - 1995 | 967% |
| 1985 - 2005 | 4989% |
| **30-year time step** | |
| 1975-2005 | 2434% |

Notes: Table shows the mean percentage change of nonzero Indonesian technical coefficients for six time-steps of lengths varying from ten to thirty years. Time steps are 1975 to 1985, 1985 to 1995, 1995 to 2005, 1975 to 1995, 1985 to 2005, and 1975 to 2005. Results were derived from an Indonesian SAM time-series (BPS, 2011).

Table 5.4 Mean percentage change of nonzero Indonesian technical coefficients in each account, broken down by type of account

| **10-year time step** | **1975 - 1985** | | **1985 - 1995** | | **1995 - 2005** | |
|---|---|---|---|---|---|---|
| **Type of account** | **Mean percentage change** | **Standard deviation of mean percentage change** | **Mean percentage change** | **Standard deviation of mean percentage change** | **Mean percentage change** | **Standard deviation of mean percentage change** |
| Domestic commodities | 125% | 185% | 133% | 314% | 31% | 20% |
| Imported commodities | 168% | 574% | 92% | 133% | 78% | 100% |
| Activities | 1047% | 2114% | 739% | 1742% | 1089% | 1555% |
| Value-added | 72% | 39% | 123% | 139% | 134% | 139% |
| Households | 558% | 196% | 463% | 359% | 167% | 128% |
| Enterprises | 38% | 0% | 79% | 0% | 4745% | 0% |
| Government | 135% | 0% | 472% | 0% | 21388% | 0% |
| **20-year time step** | | | **1975 - 1995** | | **1985 - 2005** | |
| **Type of account** | | | **Mean percentage change** | **Standard deviation of mean percentage change** | **Mean percentage change** | **Standard deviation of mean percentage change** |
| Domestic commodities | | | 218% | 413% | 221% | 541% |
| Imported commodities | | | 717% | 2998% | 100% | 152% |
| Activities | | | 1145% | 2585% | 8077% | 27238% |
| Value-added | | | 192% | 211% | 214% | 218% |
| Households | | | 1111% | 617% | 418% | 203% |
| Enterprises | | | 89% | 0% | 187% | 0% |
| Government | | | 117% | 0% | 19265% | 0% |
| **30-year time step** | | | | | **1975 - 2005** | |
| **Type of account** | | | | | **Mean percentage change** | **Standard deviation of mean percentage change** |
| Domestic commodities | | | | | 336% | 955% |
| Imported commodities | | | | | 49% | 59% |
| Activities | | | | | 3887% | 13842% |
| Value-added | | | | | 315% | 357% |
| Households | | | | | 556% | 185% |
| Enterprises | | | | | 254% | 0% |
| Government | | | | | 125% | 0% |

Notes: Table shows the mean percentage change of nonzero Indonesian technical coefficients in each of the 95 Indonesian SAM accounts, along with the standard deviations of the mean percentage changes. Results are broken down by category of account, specifically into domestic commodities, imported commodities, activities, value-added, households, enterprises, and government, and are shown for six time-steps of lengths varying from ten to thirty years. Time steps are 1975 to 1985, 1985 to 1995, 1995 to 2005, 1975 to 1995, 1985 to 2005, and 1975 to 2005. Results were derived from an Indonesian SAM time-series (BPS, 2011).

Given this evidence, is IOA useless when applied to medium to long-term time-periods?
Dietzenbacher and Hoen (2006) found that larger coefficients generally exhibited lower variance

than smaller coefficients. Thus, as larger coefficients have a greater impact on results, IOA might still generate decent predictions despite some coefficients showing large variance. Let us now empirically explore this conjecture.

### 5.3.4 Predictive power

Using the 1998 Tanzanian Leontief inverse matrix and realised exogenous data from 2001 to project 2001 account totals led to an average 12% error across the 121 account totals, with a standard deviation of 33%. Most of this error was concentrated in one account, VAT, where the prediction was off by 365%. Ignoring this account brought the average error across accounts down to 9% with a standard deviation of 8%. Table 5.5 shows the mean percentage error and the standard deviation of the latter across the accounts when broken down into categories. Predictions for government and taxation accounts are many multiples worse than predictions for other types of accounts, even when excluding VAT. The distribution of mean percentage errors across other types of accounts are perhaps indicative of the different levels of aggregation. The enterprise account outperforms all other account categories, but is a single aggregated account, while the 12 household and 13 value added accounts outperform the 43 commodities and 43 activities[108] accounts. This is consistent with existing evidence, such as Bon (1986), that predictive power improves with aggregation. Overall, with the exception of government and taxation accounts, percentage coefficient changes and percentage prediction errors were of approximately similar magnitudes for Tanzania.

Moving on to America, using the 2003, 2010 and 2003 Leontief inverse matrices and realised 2010, 2016 and 2016 exogenous data respectively to project 2010, 2016 and 2016 account totals led to 16%, 13% and 20% errors respectively, on average, across the 222 account totals, with standard deviations of 21%, 17% and 23%. IOA forecasting power, thus, appears to be significantly better than a quick glace at percentage changes in coefficients would indicate, as the mean percentage changes of nonzero US technical coefficients were 54%, 67% and 86% between 2003 and 2010, 2010 and 2016, and 2003 and 2016 respectively.

Table 5.6 shows the mean percentage errors of predictions of account totals and the standard deviations of these errors across different categories of accounts. The largest errors were found in projections of commodities, activities and value-added accounts, while projections were most reliable for households and government. The level of aggregation could be a key factor here, as there were 73, 71 and 71 commodities, activities and value-added accounts respectively, but only five household accounts and one government account. The enterprise account, however, was also a

[108] 'Activities' is a commonly used synonym for 'industries' in national accounts.

single account, yet had large projection errors across two of the time periods. This demonstrates that although predictions, in general, appear more reliable for more aggregated accounts, this is not always the case. If one compares the percentage errors in Table 5.6 with the mean percentage changes of coefficients in Table 5.2, one can see that, once again, predictions perform far better than one might assume from looking at the average extent that coefficients change. Using the 2003 technical matrix and 2010 $\boldsymbol{f}$ vectors, for example, the average mean percentage error of predictions of commodities accounts totals was 15%, while the mean percentage change in coefficients in a commodities account was 69%.

Table 5.5 – Mean percentage error and standard deviation of mean percentage error of projected versus realised 2001 Tanzanian account totals, across different categories of accounts

| **Type of account** | **Mean percentage error** | **Standard deviation of mean percentage error** |
|---|---|---|
| Commodities | 9% | 6% |
| Activities | 8% | 5% |
| Value-added | 6% | 5% |
| Households | 6% | 2% |
| Enterprises | 4% | 0% |
| Government and taxation | 87% | 125% |
| Government and taxation (excluding VAT) | 32% | 16% |

Notes: Table shows the mean percentage errors and standard deviations of mean percentage errors of projected vs. realised 2001 Tanzanian account totals. Realised account totals are taken from the appropriate Tanzanian SAM (Thurlow and Wobst, 2015). Projected account totals are calculated using the traditional Leontief demand model with the realised **f** vector from the 2001 Tanzanian SAM and the technical coefficient matrix from the 1998 SAM. Results are broken down by category of account, specifically into commodities, activities, value-added, households, enterprises, and government and taxation accounts.

When moving onto Indonesia and larger time-steps, however, predictions become less convincing. Table 5.7 shows the mean percentage errors and standard deviations across the six time-steps. Some predictive errors look tolerable. For example, when using technical coefficients from the 1975 SAM with the 2005 $\boldsymbol{f}$ vector, predictive errors in household account totals were, on average, 34%. Given the thirty-year time-scale, these predictions look reasonable. Others, however, are extremely large. Using technical coefficients from the 1975 SAM with the 2005 $\boldsymbol{f}$ vector, for example, predictive errors in activities accounts' totals were, on average, 1,090%. Some of the large average errors observed are, albeit, the result of very poor predictions in just one account. Using technical coefficients from the 1975 SAM with the 1985 $\boldsymbol{f}$ vector, for example, the total for one imported commodity account, wood and wood products, was out by 62,300%. Ignoring this account, the mean percentage error across all accounts fell from 708% to 53%, and the mean percentage error across imported commodities fell from 3065% to 102%. Similarly, using technical coefficients from the 1975 SAM with the 2005 $\boldsymbol{f}$ vector, the total for one activity, services provided by individuals, households and other services, deviated from the realised total by 23,000%. Ignoring this account, the mean percentage error across all accounts fell from 301% to 60%, and the mean percentage error across imported activities fell from 1090% to 45%.

Table 5.6 – Mean percentage error and standard deviation of mean percentage error of projected versus realised 2010 and 2016 US account totals, across different categories of accounts

| | **2003-2010** | | **2010-2016** | | **2003-2016** | |
|---|---|---|---|---|---|---|
| **Type of account** | **Mean percentage error** | **Standard deviation of mean percentage error** | **Mean percentage error** | **Standard deviation of mean percentage error** | **Mean percentage error** | **Standard deviation of mean percentage error** |
| Commodities | 15% | 17% | 15% | 22% | 19% | 21% |
| Activities | 18% | 28% | 14% | 17% | 22% | 23% |
| Value-added | 16% | 18% | 11% | 11% | 21% | 26% |
| Households | 2% | 1% | 6% | 2% | 8% | 3% |
| Enterprises | 0% | 0% | 12% | 0% | 12% | 0% |
| Government | 4% | 0% | 1% | 0% | 3% | 0% |

Notes: Table shows the mean percentage errors and standard deviations of mean percentage errors of projected vs. realised 2010 and 2016 US account totals. Realised account totals are taken from the appropriate US SAMs (constructed in Chapter 4). Projected account totals are calculated using the traditional Leontief demand model with the realised **f** vectors from the 2010 and 2016 US SAMs and the technical coefficient matrices from the 2003 and 2010 US SAMs. For example, results in the column marked '2003 – 2010' were calculated using 2003 technical coefficients and the 2010 **f** vector. Results are broken down by category of account, specifically into commodities, activities, value-added, households, enterprises, and government accounts.

Table 5.7 – Mean percentage error and standard deviation of mean percentage error of projected versus realised 1985, 1995 and 2005 Indonesian account totals, across different categories of accounts

| **10-year time step** | **1975 - 1985** | | **1985 - 1995** | | **1995 - 2005** | |
|---|---|---|---|---|---|---|
| **Type of account** | **Mean percentage error** | **Standard deviation of mean percentage error** | **Mean percentage error** | **Standard deviation of mean percentage error** | **Mean percentage change** | **Standard deviation of mean percentage error** |
| All accounts | 708% | 6356% | 56% | 198% | 66% | 283% |
| Domestic commodities | 26% | 18% | 31% | 21% | 31% | 26% |
| Imported commodities | 3065% | 13252% | 127% | 407% | 53% | 35% |
| Activities | 56% | 138% | 47% | 69% | 161% | 576% |
| Value-added | 48% | 68% | 31% | 20% | 38% | 18% |
| Households | 26% | 18% | 34% | 14% | 27% | 11% |
| Enterprises | 3% | 0% | 2% | 0% | 27% | 0% |
| Government | 15% | 0% | 2% | 0% | 16% | 0% |
| **20-year time step** | | | **1975 - 1995** | | **1985 - 2005** | |
| **Type of account** | | | **Mean percentage error** | **Standard deviation of mean percentage error** | **Mean percentage error** | **Standard deviation of mean percentage error** |
| All accounts | | | 141% | 541% | 66% | 283% |
| Domestic commodities | | | 40% | 25% | 31% | 26% |
| Imported commodities | | | 317% | 847% | 53% | 35% |
| Activities | | | 200% | 723% | 161% | 576% |
| Value-added | | | 55% | 43% | 38% | 18% |
| Households | | | 50% | 15% | 27% | 11% |
| Enterprises | | | 1% | 0% | 27% | 0% |
| Government | | | 15% | 0% | 16% | 0% |
| **30-year time step** | | | | | **1975 - 2005** | |
| **Type of account** | | | | | **Mean percentage error** | **Standard deviation of mean percentage error** |
| All accounts | | | | | 301% | 2347% |
| Domestic commodities | | | | | 41% | 41% |
| Imported commodities | | | | | 121% | 208% |
| Activities | | | | | 1090% | 4789% |
| Value-added | | | | | 48% | 31% |
| Households | | | | | 34% | 25% |
| Enterprises | | | | | 25% | 0% |
| Government | | | | | 33% | 0% |

Notes: Table shows the mean percentage errors and standard deviations of mean percentage errors of projected vs. realised 1985, 1995 and 2005 Indonesian account totals. Realised account totals are taken from the appropriate Indonesian SAMs (BPS, 2011). Projected account totals are calculated using the traditional Leontief demand model with the realised **f** vectors from the 1985, 1995 and 2005 Indonesian SAMs and the technical coefficient matrices from the 1975, 1985 and 1995 Indonesian SAMs. For example, results in the column marked '1975 – 1985' were calculated using 1975 technical coefficients and the 1985 **f** vector. Results are broken down by category of account, specifically into domestic commodities, imported commodities, activities, value-added, households, enterprises, and government accounts.

In summary, the short-term errors in predictions from the Tanzanian time series were approximately the same magnitude as changes in the technical coefficients, and both were generally reasonably small. When looking at the US time-series, which covered more medium-term time periods, predictions typically outperformed expectations given coefficient changes. While coefficient changes often seemed large, predictive errors were generally moderate. Errors in predictions were also much smaller than changes in coefficients when using the medium and longer-term time horizons from the Indonesian SAMs. They were still, however, typically sizable. While average errors could be greatly reduced by ignoring a small number of outlier accounts that had very large predictive errors, even with this adjustment, accurate medium to long-term predictions from IOA look unlikely.

As was seen when exploring changes in coefficients, government accounts sometimes generated high predictive errors; for example, in the Tanzanian time-series. This was not, however, always the case, as, for example, government accounts predictions for Indonesia were typically good. Similarly, in general, predictive errors were higher for more disaggregated accounts; although, once again, not in every case.

### 5.3.5 Constancy of relatively strongly and weakly connected sectors

While the preceding analysis casts doubt on IOA's ability to make long-term forecasts, it could still be useful for vulnerability analysis if key economic characteristics, such as the accounts relatively strongly interlinked with certain household groups, remain approximately constant over time. To explore this, the household backward linkages of each sector were calculated for each household group, and then normalised within each household group. Sectors with normalised linkages greater (or less) than one were interpreted as being relatively strongly (weakly) interconnected with that household group. Sectors in these categories were then compared at different points in time to see if relatively strongly connected sectors typically stayed relatively strongly connected, or if the sectors most important to different household groups changed with time.

Starting with Tanzania, only minor changes were observed over the four-year period. For one of the twelve household accounts there were no changes, while for the others an average of 5% of the 121 accounts changed from being relatively strongly connected to being relatively weakly connected, or vice versa. Moreover, all such changes were accounts transitioning immediately around the normalised linkages equal to one threshold, and they were mostly highly disaggregated commodities and activities accounts. Moving on the US, across the largest time-period, 2003 to 2016, 11% of accounts, on average, transitioned across the normalised linkages equal to one threshold for each household group. Once again, it was mostly very disaggregated accounts that transitioned, with, on average, 8%, 12% and 15% of commodities, activities and value-added accounts respectively transitioning. Finally, when looking at the longest time period covered by the Indonesian SAMs, 1975 to 2005, 21% of accounts, on average, transitioned across the normalised linkages equal to one threshold for each household group. Moreover, when ignoring the household group that saw 43% of accounts transition, the average was reduced to 18%. Better continuity was observed over the twenty-year time frame, with, on average, 13% of accounts transitioning. Meanwhile, changes were relatively minor over a ten-year period. Between 1995 and 2005, for example, only 8% of accounts transitioned.

These results suggest that, over short to medium time-scales, the vast majority of relatively strongly (weakly) connected sectors typically stayed relatively strongly (weakly) connected. Moreover, for all except one household group, this was also true over even a thirty-year period. Key economic attributes are, thus, retained even over time-horizons where predictions can become spurious.

### 5.3.6 Reflections on stability analysis

These empirical tests suggest that IOA's assumption of fixed production coefficients is a decent approximation only over a short time-scale. While Tanzanian coefficients changed between 1998 and 2001, the changes were relatively small. When looking at the US' six and seven-year time-periods, however, average coefficient changes were multiples larger, and, in the longer time-horizons considered for Indonesia, coefficients sometimes changed by thousands of percent.

In light of often sizable coefficient changes, one might expect IOA to have poor predictive power. However, predictions were found to be generally reasonable in the short and medium-term. When looking at longer time-scales, the empirical analysis in this chapter found that many accounts were still reasonably well predicted. However, others saw errors of over a thousand percent. Thus, it seems unlikely that IOA can be used to confidently generate meaningful medium to long-term predictions. This is, however, not surprising, given the observation in Chapter 3 that most macroeconomic models struggle to make such predications – a consequence of modelling complex, dynamic nonlinear systems.

The empirical analysis thus indicates that IOA works in practice, albeit not in theory, over short and medium time-horizons, and thus can be used to generate plausible scenarios of economic responses to climate change impacts in a given year. As the SAMs, however, change significantly over the medium to long-term, the results from the case studies in Chapters 6 and 7, which extend out to 2100 and 2050 respectively, should be viewed as plausible scenarios, not predictions.

The empirical analysis does, however, also suggest that some economic characteristics, such as which accounts are relatively strongly or weakly interlinked with certain household groups, remain approximately constant over time. This suggests that IOA could be useful for scoping out vulnerabilities, even over time-horizons where predictions become meaningless. However, given the long time-scales of the case studies in Chapter 6 and 7, results generated for more than a decade or two in the future should not be viewed as a vulnerability analysis for any specific country. Results for all countries should instead be considered collectively to explore if any patterns emerge or if climate change induced inequality varies according to characteristics of economies.

Finally, as extremely large coefficient changes were observed in inventories, such accounts, in addition to the usual statistical discrepancy, ROW and capital accounts, were assumed exogenous in all IOA in Chapters 6 and 7. Similarly, on occasions, the government account produced sizable discrepancies. This corroborated the commonly held view that government spending patterns, like ROW spending patterns, frequently alter for reasons beyond the domestic economy, and so government accounts were also be taken to exogenous in all subsequent IOA.

## 5.4 Summary

This chapter explained how IOA will be used to bring economic inequality into coupled economic-environmental models, and empirically tested IOA's assumption of fixed production recipes, to explore how the methodology performs as an economic model.

The chapter first detailed the linear algebra of traditional IOA, which can be used to model the direct and indirect effects of changes in demand. The chapter then gave an overview of how economists have adapted IOA so that it can model effects stemming from supply changes. These extensions include the Ghosh and MEE models, partial hypothetical extraction and dynamic IOA based models. The chapter then outlined the coupling methodology used in the case studies in Chapters 6 and 7 to bring economic inequality into coupled economic-environmental models. Quantity models are used, as it is quantity changes that are driving economic change. The traditional Leontief model was used for changes in final demand, while the MEE model was used for output changes. The MEE model was chosen because the Ghosh quantity model has been widely discredited, partial hypothetical extraction assumes that imports can compensate for reduced domestic production, and dynamic IOA based models estimate how an economy recovers from once-off events, not how it adjusts to long-term changes.

To empirically test the key IOA assumption of fixed technical coefficients, this chapter used SAM time-series for Tanzania, Indonesia and the US. Firstly, percentage changes in technical coefficients were calculated. IOA was then used to forecast account totals using SAM technical coefficient matrices and final demand vectors from different years. Finally, household backward linkages were calculated and normalised within a household group to see which accounts were relatively strongly and weakly connected with each household group.

This empirical analysis indicated that IOA's assumption of fixed allocation coefficients is, beyond the short term, a crude assumption that puts the model at a disadvantage to others, such as computable general equilibrium (CGE) models, that are nonlinear and so allow the economy to adapt to an exogenous change. The model, however, still generates decent predictions over the short and medium term, and so can be used to generate plausible scenarios of economic responses to climate change impacts in a given year. In addition, general characteristics, such as which accounts are relatively strongly and weakly connected with each household group, appear to be preserved for a couple of decades, which is useful for vulnerability analysis. The results, however, demonstrate that economies change considerably over longer time horizons. Thus, after a decade or two, economies are likely to be sufficiently different from SAMs that results should not be viewed as a vulnerability analysis for any specific country. Instead, lessons should be drawn from a cross-country analysis to see if any general patterns emerge or to explore how responses to exogenous changes vary according to characteristics of economies.

As explored in Chapter 3, for addressing the research questions outlined in Chapter 2, IOA has many advantages over other models. This chapter has demonstrated that IOA's primary disadvantage, fixed allocation coefficients, is workable in practice, if not in theory, providing one interprets the results as plausible scenarios, not predictions, which should be viewed collectively across countries, rather than interpreted as impact or vulnerability analyses for specific countries. As this key disadvantage can thus be managed, IOA appears to be the most appropriate macroeconomic tool for this thesis.

# Chapter 6 – Impact of climate change on income inequality in Egypt, Ethiopia, India, Mexico, the United States, Vietnam and Zambia

This chapter presents the first case study, which uses the popular integrated assessment model (IAM) the 'Climate Framework for Uncertainty, Negotiation and Distribution' (FUND) (Anthoff and Tol, 2014a) to explore the impact of climate change on income inequality in seven countries. A description of the model is provided in Section 6.1, along with the methodology used to implement the case study, such as how the coupling methodology outlined in Chapter 5 was applied, how regional results were disaggregated to estimate country-level impacts, how budget constraints were imposed, and how scenarios were generated. Section 6.2 explains FUND's impact functions and explores the estimated impacts used in the case study, while case study results are presented in Section 6.3. These results are analysed in Chapter 8, as this enabled results from the Alaska case study in Chapter 7 to also be used to address the research questions outlined in Chapter 2.

## 6.1 Introduction and methodology

### 6.1.1 FUND overview

As explained in Chapter 3, FUND is an IAM that aims to estimate the economic consequences of different greenhouse gas (GHG) emissions trajectories, along with mitigation and adaptation strategies. FUND divides the world into 16 regions[109], and estimates regional impacts on agriculture, forestry, water resources, energy consumption, wetland loss, dryland loss, cost of coastal protection, ecosystems, morbidity and mortality from health impacts and tropical and extratropical storms, and economic damages due to tropical and extratropical storms. Sector impacts that are not readily measured in monetary units, such as mortality, are valued in dollars using the hedonic pricing and contingent valuation techniques described in Chapter 3.

FUND estimates annual climate change impacts from[110] 1950 to 3000. The IAM uses exogenous projections of population growth, per capita income growth and technological progress for four scenarios from the Intergovernmental Panel on Climate Change's (IPCC's) Special Report on Emissions Scenarios (SRES) (IPCC, 2000); specifically, SRES A1B, A2, B1 and B2. This exogenous data was taken from the Integrated Model to Assess the Global Environment (IMAGE)[111] (van Vuuren et

[109] For a list of the countries included in each region, see (Anthoff and Tol, 2014b).
[110] FUND must be run from 1950 onwards to initiate the climate component of the model.
[111] Although FUND assumes a steady-state from 2300 onwards, with constant populations and per capita income growth rates.

al., 2011b). Using the dichotomy established in Chapter 3, IMAGE falls into the first category of IAMs, i.e. is large, complex, computationally intensive, and focused on deriving scenarios for different demographic, economic and technological futures and associated GHG emission trajectories and their impact on climate variables and the biosphere. FUND, in contrast, is in the second category of IAMs, as it is primarily focused on economic consequences, and is much smaller and simpler. FUND uses the IMAGE data as exogenous inputs into simple emissions, atmospheric gas concentrations[112], radiative forcing, temperature and sea-level rise (SLR) models[113]. Regional, sector-level economic damage functions then estimate the cumulative monetary costs and benefits of the projected changes in temperature, GHG concentrations, SLR, income and population. As explained in Chapter 3, these damage functions are derived from a pool of external impact studies.

73 uncertain variables are modelled probabilistically using Monte Carlo simulations, and are drawn from a mixture of normal, truncated normal, triangular, exponential and gamma distributions, as specified in Anthoff and Tol (2014b). FUND 3.9, the most recent version of the model, was used in this thesis, and the technical documentation, which includes a list of all the impact studies used to estimate each damage function, can be found in Anthoff and Tol (2014a).

### 6.1.2 Applying coupling methodology outlined in Chapter 5

As explained in Chapter 5, the impacts of a mixture of exogenous demand changes and exogenous output changes can be modelled using equation (5.4), i.e.

$$\begin{pmatrix} \Delta\boldsymbol{x}^{(en)} \\ \Delta\boldsymbol{f}^{(en)} \end{pmatrix} = \boldsymbol{M}^{-1}\boldsymbol{N}\begin{pmatrix} \Delta\boldsymbol{f}^{(ex)} \\ \Delta\boldsymbol{x}^{(ex)} \end{pmatrix},$$

where $\boldsymbol{M} = \begin{bmatrix} (\boldsymbol{I}-\boldsymbol{A_{11}}) & \boldsymbol{0} \\ -\boldsymbol{A_{21}} & -\boldsymbol{I} \end{bmatrix}$ and $\boldsymbol{N} = \begin{bmatrix} \boldsymbol{I} & \boldsymbol{A_{12}} \\ \boldsymbol{0} & (\boldsymbol{A_{22}}-\boldsymbol{I}) \end{bmatrix}$. If the matrix of technical coefficients, $\boldsymbol{A}$, is arranged so that the $n$ row and column accounts with endogenous account totals are at the top and left respectively, with the remaining $m-n$ accounts with exogenous account totals at the bottom and right respectively, then $\boldsymbol{A_{11}}$, $\boldsymbol{A_{12}}$, $\boldsymbol{A_{21}}$ and $\boldsymbol{A_{22}}$ are matrices containing the technical coefficients in rows $1$ to $n$, $1$ to $n$, $n+1$ to $m$, and $n+1$ to $m$ respectively, and columns $1$ to $n$, $n+1$ to $m$, $1$ to $n$, and $n+1$ to $m$ respectively of $\boldsymbol{A}$. $\boldsymbol{I}$ and $\boldsymbol{0}$ are appropriately sized identity and null matrices respectively. $\boldsymbol{x}^{(en)}$, $\boldsymbol{x}^{(ex)}$, $\boldsymbol{f}^{(ex)}$ and $\boldsymbol{f}^{(en)}$ are vectors of endogenous account totals, exogenous account totals, exogenous final demand and endogenous final demand respectively. The inventories, rest-of-the-world (ROW), capital-savings, government and statistical discrepancy accounts were

[112] FUND models atmospheric concentrations of carbon dioxide, methane, nitrous oxide and sulfur hexafluoride.

[113] Although emissions from land use changes and deforestation, and radiative forcing from sulphur dioxide are also specified exogenously for each scenario.

assumed to lie outside of the model and so comprised final demand. The reasoning behind this was detailed in Chapter 5.

As $(5.4)$ was derived from

$$\left(\begin{bmatrix} \boldsymbol{I} & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{I} \end{bmatrix} - \begin{bmatrix} \boldsymbol{A}_{11} & \boldsymbol{A}_{12} \\ \boldsymbol{A}_{21} & \boldsymbol{A}_{22} \end{bmatrix}\right)\begin{pmatrix} \boldsymbol{x}^{(en)} \\ \boldsymbol{x}^{(ex)} \end{pmatrix} = \begin{pmatrix} \boldsymbol{f}^{(ex)} \\ \boldsymbol{f}^{(en)} \end{pmatrix},$$

and changes to household incomes could be seen in the vector of account totals, $\begin{pmatrix} \boldsymbol{x}^{(en)} \\ \boldsymbol{x}^{(ex)} \end{pmatrix}$, there was no need to calculate $\boldsymbol{f}^{(en)}$, as one could determine $\boldsymbol{x}^{(en)}$ from

$$(\boldsymbol{I} - \boldsymbol{A}_{11})\boldsymbol{x}^{(en)} - \boldsymbol{A}_{12}\boldsymbol{x}^{(ex)} = \boldsymbol{f}^{(ex)}.$$

As the above is a linear model and $\boldsymbol{A}$ is assumed to be constant,

$$\Delta\boldsymbol{x}^{(en)} = (\boldsymbol{I} - \boldsymbol{A}_{11})^{-1}\left(\Delta\boldsymbol{f}^{(ex)} + \boldsymbol{A}_{12}\Delta\boldsymbol{x}^{(ex)}\right).$$

FUND's estimated changes in agricultural production, the monetary value of available water resources, expenditure on space heating and cooling, expenditure on coastal protection, and economic damages from tropical and extratropical storms were economic costs or benefits, and so were easily incorporated into this framework. Changes in agricultural production and water resources were commodity output changes, and so could form the $\Delta\boldsymbol{x}^{(ex)}$ vector. Meanwhile, expenditure on space heating and cooling, coastal protection, and repairing economic damages from tropical and extratropical storms were demand changes, and so formed part[114] of the $\Delta\boldsymbol{f}^{(ex)}$ vector.

Energy expenditures were assumed to be paid to the electricity commodity account, while expenditures on coastal protection and repairing storm damages were assumed to be paid to the construction commodity account. The storm damage repairs analysis also assumed that storm damages were valued at replacement cost[115]. Coastal protection was assumed to be entirely funded by the government current account, while storm damage repairs were modelled as funded by the investment account, and so assumed collective household, enterprise and government funding. Changes in energy *consumption* could not be modelled, as this would require changing business activities' and household's technical coefficients. The latter cannot be accommodated in an input-output framework, so changes in energy expenditure were instead modelled as changes in investment account spending on electricity. This could be implemented, as spending from capital-

[114] Another component of the $\Delta\boldsymbol{f}^{(ex)}$ vector was determined by imposing a budget constraint. See section 6.1.4 of this chapter for details.

[115] The EM-DAT database (CRED, 2018), which was used to calibrate FUND's storm damage functions, does not explain how damages were valued. Damages may be valued inconsistently in the database across different disasters, as the data was compiled from many different sources.

savings accounts formed part of final demand.

FUND's forestry impact estimates could not be included in the analysis, as FUND's output for this sector estimates changes to producer and consumer surplus. As discussed in Chapter 5, the latter is the end-point of an analysis into the economic effects of climate change on forestry, not a driving force, and so should not be used as an input in input-output analysis (IOA). The force driving effects is the change in forestry yields, which FUND does not estimate.

Similarly, while hedonic pricing and contingent valuation techniques have been used to monetise impacts on health and ecosystems, such estimates cannot readily be interpreted as either changes in spending or production. IOA was designed to estimate the effects of economic changes to economic systems; it cannot model effects due to aspects of life that are not traded on markets. These sectors were thus not considered in this thesis.

Moving onto dryland and wetland[116] losses, the value of dryland is assumed in FUND to be proportional to the income density in that region, and wetland value is assumed to be proportional to regional population and income density. It is not clear, however, how the values of lost wetlands and drylands from SLR could be used as inputs in an IOA. While a reduction in available dryland could reduce production in sectors that operated on that land, incorporating this would require a coastal land use analysis to determine which sectors would be affected. This was beyond the time-scope of this project. Meanwhile, wetlands are of great importance to ecosystems, but limited *direct* importance to economies, so it is also unclear how such damages could be assigned to a given sector in a SAM. Finally, FUND gives back-of-the-envelope estimates of the cost of immigration and emigration due to SLR. The estimated cost of each immigrant or emigrant and the number of people forced to move is, however, not robust, as no substantial analysis takes place. These guesses were thus excluded from this thesis.

This case study consequently considers only five of FUND's impact categories: changes in agricultural production, water resources, expenditure on space heating and cooling, expenditure on coastal protection, and economic damages from tropical and extratropical storms. In FUND, the first three of these impact categories generally dominate all other tangible economic damages, including the tangible economic damages that were not considered in this case study. Between 2020 and 2100 in the A1B scenario for the United States (US), for example, the five impacts listed above represented, on average, 90.6% of FUND total impacts. In 65% of years, the five impacts collectively represented

[116] Wetlands contain soil that is saturated with water for at least part of the year, which results in distinctive vegetation that has adapted to these conditions. In FUND, drylands are defined to be lands that are not wetlands.

more than 95% of total impacts, and only in the few years where total impacts were small due to the larger agricultural, water or energy impacts cancelling each other out, did other impact categories make a sizable contribution towards the total tangible impacts. This suggests that the most significant drivers of climate change impacts were captured in this case study.

### 6.1.3 Disaggregating regional impacts

FUND estimates impacts for 16 regions, and these typically include multiple countries. For example, the Central America region contains Belize, Costa Rica, El Salvador, Guatemala, Honduras, Mexico, Nicaragua, and Panama. The US and Canada regions are exceptions, as they each contain only one country. Regional impacts thus generally needed to be disaggregated into country-level impacts. FUND models average temperature for a region; there is no higher resolution analysis that is then aggregated up to the regional level. As such, regional impacts are assumed to proportionately apply to all countries in the region. The fractional reduction in agricultural production, for example, is explicitly "assumed to hold for each country in the respective regions" (Anthoff and Tol, 2014a). In this thesis, regional impacts were thus disaggregated in proportion to a country's sector size versus the total size of that sector aggregated across all countries in the region.

For agricultural production impacts, regional data was disaggregated between countries in proportion to each country's percentage of regional agricultural value-added. Value-added data was taken from the World Bank (World Bank, 2018). The same approach was taken for water resources, energy consumption, coastal protection, and repairing storm damages, using, respectively, data on total renewable water resources, taken from the Food and Agriculture Organization of the United Nations' (FAO's) Aquastat database (FAO, 2018), electricity consumption in kilowatt hours (kWh), taken from the US Central Intelligence Agency's World Factbook (CIA, 2018), 2010 population living in a less than one meter high[117] low elevation coastal zone (LECZ), available from Columbia University's Center for International Earth Science and Information Network (CESIN, 2013), and total damages from storms between 2000 and 2018, valued in 2000 USD, from the Centre for Research on the Epidemiology of Disasters (CRED) at the Université Catholique de Louvain's Emergency Events Database (EM-DAT) (CRED, 2018).

### 6.1.4 Budget constraints

It was crucial to impose a budget constraint on a domestic institution with projected increases in climate change related expenditures, or any increase in expenditure in $\Delta\boldsymbol{f}_{ex}$ would always result in economic growth. A change in expenditure thus had to be funded through changed savings,

[117] FUND's largest SLR projection across the four scenarios is 0.8m.

borrowing, or expenditure on other goods and services. Only the latter was modelled in this thesis, as the first two options would require an endogenous capital-savings account. As discussed in Chapter 5, such accounts are typically assumed to be exogenous, due to concerns around technical coefficient variability. In addition, as explained in section 6.1.2 of this chapter, this account was assumed to be determined outside of the model so that investment could be a component of final demand. This was needed to explore the impacts of changes in expenditures on energy and storm repairs.

As per section 6.1.2 of this chapter, depending on the type of expenditure, changes in expenditure were funded by government or investment. It was assumed that an increase (decrease) in expenditure on energy or construction by government or investment was funded by a decrease (increase) in spending on all other commodities purchased by government or investment, with this change spread across commodities in proportion to government or investment's spending on those services in the SAM.

### 6.1.5 Scenarios

As discussed, FUND is set-up to model four scenarios, SRES A1B, A2, B1 and B2. While FUND runs until 3000 so that larger climate change effects can be explored, this time-scale was deemed inappropriate for economically-focused research questions. One has no idea what economies will look like in a thousand years, and it is doubtful that much can be learnt from speculating, so this case study explored cumulative impacts in annual time-steps from 2020 to 2100. The latter is a common cut-off point for IAM studies of climate change. Moreover, considering the vast economic and technological changes that occurred between 1930 and 2010, economies beyond the end of the century are unlikely to share many similarities with those today. Modelling even up to this point is already highly speculative, but it does allow exploration of the possible impacts of more sizable climate change effects. This is only useful, however, if results are understood to be exploratory.

As discussed in Chapters 3 and 5, the results generated in this case study are not predictions, but rather scenarios to help explore uncertainty. Firstly, as discussed in Chapter 3, results from IAMs should never be treated as precise predictions, due to the difficulties of modelling complex, dynamic nonlinear systems, such as the climate and economies. The stability analysis in Chapter 5 also illustrated that IOA struggles to make precise predictions over long time-horizons. Chapter 5 suggested that key structural properties of an economy, such as the relative interconnectedness of sectors with households, can sometimes be maintained for longer periods, which is useful for vulnerability analysis. The maximum, thirty-year, time horizon explored in Chapter 5, however, is much shorter than the proposed eighty-year analysis for this case study. As such, results from the latter half of this time period should be viewed as particularly exploratory. They should be approached as an exploration of vulnerabilities across economies, rather than predictions or vulnerability analyses for seven specific countries. IOA provides a plausible model of how economies could react to exogenous unit changes to certain sectors, while the FUND model gives an indication of possible relative magnitudes of the exogenous changes to sectors. All results should be viewed in this light.

Let $t$ represent the time period, $r$ the FUND region containing the country, $c$, of interest, and $s$ the SRES scenario being explored. When moving from one time period to the next, to get the region's income in $t$ before climate impacts in $t$ are considered, FUND inflates the region's $t-1$ income by $\left(1+g^{(r,s)}{}_{t}\right)$. Specifically,

$$\left(1+g^{(r,s)}{}_{t}\right)=\left(1+pgrowth^{(r,s)}{}_{t-1}\right)\left(1+ypcgrowth^{(r,s)}{}_{t-1}\right),$$

where $pgrowth$ and $ypcgrowth$ are, respectively, annual population and income per capita growth rates. As discussed, $pgrowth$ and $ypcgrowth$ are specified exogenously for each region, scenario and time period. All of FUND's estimated impacts and incomes are quoted in 1995 USD billions, and, as outlined in Chapter 4, all SAMs used in this case study were converted into 1995 USD billions. In this case study, it was thus assumed that all parts of a country's economy grew by $\gamma^{(r,s)}{}_{t}=\left(1+g^{(r,s)}{}_{t}\right)$ between $t-1$ and $t$. For ease of notation, the $(r,s)$ superscript will be dropped from subsequent notation; however, it should be remembered that $\gamma_t$ and $g_t$ varied by region and scenario.

Meanwhile, let $\boldsymbol{x}^{(c,s)}{}_{t}=\begin{pmatrix}\boldsymbol{x}^{(c,s,en)}{}_{t}\\ \boldsymbol{x}^{(c,s,ex)}{}_{t}\end{pmatrix}$ represent the vector of account totals for a given country and scenario at time $t$, after climate impacts in time $t$ have been taken into account. Similarly, let $\Delta\boldsymbol{x}^{(c,s)}{}_{t}=\begin{pmatrix}\Delta\boldsymbol{x}^{(c,s,en)}{}_{t}\\ \Delta\boldsymbol{x}^{(c,s,ex)}{}_{t}\end{pmatrix}$ represent the vector of changes in account totals at time $t$ due to climate impacts for the given country and scenario at time $t$. Once again, for ease of notation, the $(c,s)$ superscript will be dropped from subsequent notation; however, it should be remembered that $\boldsymbol{x}_t$ and $\Delta\boldsymbol{x}_t$ varied by country and scenario.

To get $\boldsymbol{x}_t$ for the first year of analysis, $t=2020$, the vector of SAM account totals, $\boldsymbol{x}_{SAM}$, was inflated using the growth rates for each year, from the year after the SAM year, $t=SAM$, to 2020, such that

$$\boldsymbol{x}_{2020}=\boldsymbol{x}_{SAM}\prod_{i=SAM+1}^{2020}\gamma_i+\Delta\boldsymbol{x}_{2020}.$$

Where the SAM straddled two years, the SAM year was taken to be the lower of the two years, and the growth rate in year $SAM + 1$ was taken to be half the FUND growth rate for that year.

FUND's estimated impacts at each time period are cumulative impacts from a counterfactual economic baseline, $\widetilde{\boldsymbol{x}}_t$, where populations and incomes are consistent with the given SRES scenario, however, there have hitherto been no economic impacts from climate change. This meant that

$$\boldsymbol{x}_t = \boldsymbol{x}_{SAM} \prod_{i=SAM}^{t} \gamma_i + \Delta\boldsymbol{x}_t,$$

where

$$\Delta\boldsymbol{x}_t = \begin{pmatrix} \Delta\boldsymbol{x}^{(en)}{}_t \\ \Delta\boldsymbol{x}^{(ex)}{}_t \end{pmatrix} = \begin{pmatrix} (\boldsymbol{I} - \boldsymbol{A}_{11})^{-1}\left(\Delta\boldsymbol{f}^{(ex)}{}_t + \boldsymbol{A}_{12}\Delta\boldsymbol{x}^{(ex)}{}_t\right) \\ \Delta\boldsymbol{x}^{(ex)}{}_t \end{pmatrix}.$$

Meanwhile, the counterfactual economic baseline, $\widetilde{\boldsymbol{x}}_t$, was calculated using

$$\widetilde{\boldsymbol{x}}_t = \boldsymbol{x}_{SAM} \prod_{i=SAM}^{t} \gamma_i.$$

Once again, $\widetilde{\boldsymbol{x}}_t$ differed across countries and scenarios; however, for ease of notation, the $(c, s)$ superscript has been omitted.

Time series of inequality ratios were determined from the generated $\boldsymbol{x}_t$ time series. As an example, assume that the household quintiles' account totals formed the first five entries of $\boldsymbol{x}_t$, with the bottom quintile, Q1, and top quintile, Q5, in rows 1 and 5 respectively. If $x^{(u)}{}_t$ represents the $u^{\text{th}}$ entry in $\boldsymbol{x}_t$ then, for the given country and scenario,

$$(Q5/Q1)_t = \frac{x^{(5)}{}_t}{x^{(1)}{}_t}.$$

These could be compared to the equivalent baseline ratios, e.g.

$$\left(\widetilde{Q5}/\widetilde{Q1}\right) = \frac{\tilde{x}^{(5)}}{\tilde{x}^{(1)}},$$

to explore changes in the ratios over time. Note that that baseline ratios were those in the SAMs, as a growth rate applied to the whole SAM would not affect these ratios.

To assess whether $\Delta x^{(u)}{}_t$ was large or small for each household group, percentage changes, $P^{(u)}{}_t$, were introduced that, as usual, varied across countries and scenarios. These explored cumulative climate impacts at $t$ as percentages of the baseline incomes at $t$, i.e.

$$P^{(u)}{}_t = \frac{\Delta x^{(u)}{}_t}{\tilde{x}^{(u)}{}_t}.$$

They captured the proportion of baseline income at time $t$ that was gained or lost due to cumulative climate change impacts at $t$.

### 6.1.6 Other methodological notes

Uncertain variables, including damage function parameters, are modelled probabilistically in FUND using Monte Carlo simulations, where a 'best-guess' for each parameter is suggested along with a range of plausible values and accompanying PDF. As discussed in Chapter 3, probabilistic modelling was deemed inappropriate for this thesis, and a scenario analysis approach was instead adopted. As such, only best guess impacts were used for each scenario.

The most recent US SAM, for 2016, was used for all the US estimates in this case study. However, Chapter 8 features an analysis of how results were affected by using earlier or alternatively disaggregated US SAMs.

## 6.2 FUND-estimated sector impacts

### 6.2.1 Introduction to FUND impact functions

Graphs of FUND estimated impacts for all countries, scenarios and sectors can be found in Appendix G.

FUND has three agricultural impact functions, which are dependent on the rate of climate change, the level of climate change, and $CO_2$ fertilisation respectively. The first and last of these are always negative and positive respectively, while level effects can be negative or positive depending on whether the regional temperature exceeds the specified optimal temperature for the given region. $CO_2$ fertilisation is a logarithmic function, so there are diminishing marginal benefits to increased $CO_2$. The agricultural impact functions also depend on regional income per capita growth, specifically, the ratio of income per capita in the year in question to that in 1990, the calibration year. This is because the value of impacts will change as the economy grows overall. The calibration coefficients for all FUND sector impact functions differ by region.

While the optimal regional warming above preindustrial times was projected to be exceeded by 2100 in all regions and scenarios, impacts on agriculture were positive throughout the period for all countries in the study, as $CO_2$ fertilisation still dominated rate and level effects at 2100. Benefits to agriculture in Ethiopia in A1B, for example, started at 0.6 1995 USD billions in 2020, rose to a maximum of 3.5 1995 USD billions in 2073, and then fell to 1.7 1995 USD billions in 2100. All countries and scenarios followed this pattern of rising to a peak and then falling during the time period. All end points were positive and at a higher level at 2100 than 2020.

The FUND water resources impact function depends on regional income per capita growth, regional population growth and global mean surface temperature (GMST). For a GMST higher than preindustrial levels, it always produces negative impacts. As can be seen in Appendix G, impacts became more negative as time progressed in all countries and scenarios. In India in B1, for example, direct impacts were -1.02 1995 USD billions in 2020, and -16.86 1995 USD billions in 2100.

FUND models changes in energy consumption for space heating and cooling separately. Both are functions of regional population growth, regional income per capita growth, and GMST. Savings from reduced space heating display decreasing marginal benefits from temperature rises, which saturate. The costs of increased space cooling, however, do not saturate. As can be seen in Appendix G, the net change in energy expenditure was positive, i.e. increasing, for Egypt, Ethiopia, and Zambia throughout 2020 to 2100 in all scenarios. For India and Vietnam, the net change was negative in 2020 in A2, but then positive for all other years, and in all other scenarios. For Mexico, there were net energy savings in all scenarios for twenty to twenty-five years, before increased space cooling costs started dominating reduced space heating benefits. In the US, there were projected net savings for the first 35 to 45 years, depending on the scenario, before net increases in energy expenditures.

The level of coastal protection in FUND is determined by a cost-benefit analysis (CBA) that accounts for the cost of coastal protection and the value of wetland and dryland lost. The cost of coastal protection depends on costs per unit of protection, the SLR, the rate of pure time preference, and the consumption elasticity of marginal utility[118]. Meanwhile, the value of wetland lost is a function of income per capita, SLR and degree of coastal protection, and the value of dryland lost depends on income per square kilometre and lost land area. As discussed, only the costs of coastal protection were included in the impacts analysis in this case study. In addition, Ethiopia and Zambia are landlocked countries, and so were assumed to experience no SLR impacts.

FUND's economic damages from tropical storms impact function is dependent on the increase in regional income per capita and temperature, while FUND's economic damages from extratropical storms impact function is dependent on regional income per capita and atmospheric $CO_2$ concentration. Damages from tropical and extratropical storms were summed and so taken

[118] The FUND default pure rate of time preference and consumption elasticity of marginal utility were used for this case study, i.e. these values were 1% and 1 respectively.

collectively in this case study. The historical storm data from (CRED, 2018) suggested that storms damages in Sub-Saharan Africa have been overwhelmingly concentrated in South-Eastern countries, such as Madagascar, South Africa, Zimbabwe and Mozambique. Historical storm damages in Ethiopia and Zambia have been negligible in comparison. These countries, thus, were allocated a similarly negligible percentage of the FUND SSA region's storm damages. Likewise, while Egypt was allocated 29% of its region's estimated storm damage costs, the latter were so minimal that estimated storm damage repair costs in Egypt were also negligible.

The estimated costs of coastal protection and storm damages were generally much smaller than all other impacts in all countries and scenarios, even though they increased over the 2020 to 2100 period in all countries and scenarios.

Before exploring the impacts estimated by FUND, one should note that the pools of impact studies that underpin FUND's, and all prominent IAM's, impact functions are generally not updated regularly (Prieg and Yumashev, forthcoming). This means that impact functions do not always reflect current expertise. Important examples of this are FUND's agricultural impacts functions. The agricultural impact studies used for calibration and to establish functional forms were published between 1992 and 1996. The literature on the impact of climate change on agriculture has moved on considerably since then, and this has led to criticism of FUND's agricultural impacts functions; for example, see Ackerman and Munitz (2012).

Concerns particularly surround FUND's estimated impacts of $CO_2$ fertilisation on agricultural yields. Older impact studies typically estimate a much greater positive impact than more recent studies. This is because early experiments took place in enclosed greenhouses rather than in the open air using more recent technological innovations, such as free-air concentration enrichment (FACE) technology (Long et al., 2006). Long et al. (2006), for example, suggests that benefits from $CO_2$ enrichment could be 50% lower than earlier estimates. Other studies raise doubts about FUND's level of climate change agricultural impact function. Schlenker and Roberts (2009), for example, indicates that once the optimal temperature has been past, benefits should fall away and turn to costs at a much faster rate than the quadratic function specified in FUND. Schlenker and Roberts (2009) also casts doubt on the degree of agricultural adaptation to climate change assumed in FUND.

These criticisms are important as FUND's agricultural impacts are large in comparison to many other sectors, and so have a strong influence on results. As discussed, FUND's estimate impacts on agriculture were positive throughout the period for all countries in the study, despite the optimal regional temperature above preindustrial times being exceeded in all regions and scenarios by 2100. This result is also contrary to observations that climate change is already having a negative impact on global agricultural production (Lobell et al., 2011). With more moderate benefits from $CO_2$ fertilisation, level-related costs emerging rapidly after the optimal temperature is exceeded, and less optimistic adaptation assumptions, FUND could project agricultural costs rather than benefits.

The impact of FUND's assumptions on results will be discussed further in Chapter 9.

### 6.2.2 How large are FUND-estimated impacts?

To explore whether FUND-estimated sector impacts were large or small, for changes to agriculture or water output, one can express the FUND-estimated impact at each time as a percentage of the given commodity's base output at that time. Similarly, for FUND-estimated changes to electricity or construction expenditure, one can express the IOA estimated change in the given sector's output due to the final demand change, at each time, as a percentage of the given commodity's base output at that time. Table 6.1 shows, for the given countries and scenarios, the largest cumulative percentage change in output observed in any year between 2020 and 2100, for the five FUND impact categories explored in this case study.

Table 6.1 – Largest estimated cumulative percentage change in output for the applicable commodity (agriculture, water, electricity or construction) compared to the base output for that commodity, in any year between 2020 and 2100

| Agriculture | | | | |
|---|---|---|---|---|
| **Country** | **A1B** | **A2** | **B1** | **B2** |
| Egypt | 4.7% | 4.7% | 4.5% | 4.2% |
| Ethiopia | 3.6% | 3.6% | 3.4% | 3.2% |
| India | 4.3% | 4.6% | 4.3% | 4.3% |
| Mexico | 11.2% | 11.7% | 10.9% | 10.6% |
| US | 8.2% | 8.0% | 7.6% | 7.3% |
| Vietnam | 11.0% | 11.7% | 10.9% | 10.9% |
| Zambia | 0.8% | 0.8% | 0.8% | 0.8% |

| Water | | | | |
|---|---|---|---|---|
| **Country** | **A1B** | **A2** | **B1** | **B2** |
| Egypt | -116.2% | -91.3% | -107.1% | -100.0% |
| Ethiopia | -12.0% | -9.4% | -11% | -10.4% |
| India | -33.4% | -27.5% | -31.4% | -34.9% |
| Mexico | -12.6% | -10.4% | -11.7% | -11.5% |
| US | -127.5% | -103.2% | -127.6% | -126.1% |
| Vietnam | -191.6% | -159.8% | -181.2% | -201.1% |
| Zambia | -22.1% | -18.7% | -20.9% | -20.7% |

| Energy | | | | |
|---|---|---|---|---|
| **Country** | **A1B** | **A2** | **B1** | **B2** |
| Egypt | 37.0% | 43.2% | 27.7% | 48.5% |
| Ethiopia | 32.9% | 38.5% | 24.3% | 43.3% |
| India | 7.3% | 7.1% | 2.2% | 13.0% |
| Mexico | 2.6% | 2.8% | -1.7% | 3.5% |
| US | 8.8% | 6.7% | -6.4% | 11.9% |
| Vietnam | 27.9% | 27.4% | 8.5% | 50% |
| Zambia | 19.0% | 23.9% | 14.5% | 27.2% |

| SLR | | | | |
|---|---|---|---|---|
| **Country** | **A1B** | **A2** | **B1** | **B2** |
| Egypt | 0.2% | 0.3% | 0.3% | 0.3% |
| India | 0.1% | 0.1% | 0.1% | 0.1% |
| Mexico | 0.1% | 0.1% | 0.1% | 0.1% |
| US | 0.0% | 0.0% | 0.0% | 0.1% |
| Vietnam | 0.8% | 1.3% | 1.1% | 1.0% |

| Storms | | | | |
|---|---|---|---|---|
| **Country** | **A1B** | **A2** | **B1** | **B2** |
| Egypt | 0.0% | 0.0% | 0.0% | 0.0% |
| India | 0.1% | 0.1% | 0.1% | 0.1% |
| Mexico | 0.1% | 0.1% | 0.1% | 0.1% |
| US | 0.3% | 0.3% | 0.4% | 0.4% |
| Vietnam | 0.0% | 0.1% | 0.1% | 0.1% |

Notes: To explore how large FUND's estimated impacts are in proportion to economies, the table shows FUND's largest estimated impacts observed in any year between 2020 and 2100, as a percentage of base agricultural or water commodity output, or base electricity, construction or construction expenditure, for agricultural, water, energy, SLR and storms impacts estimates respectively. Agricultural and water impacts are commodity output changes, where positive (negative) numbers indicate increases (decreases) in output. Meanwhile, energy, SLR and storms impacts are changes in final demand, where positive (negative) numbers indicate increases (decreases) in expenditure. Note that an increase in expenditure does not necessarily produce an increase in economic growth, as budget constraints were imposed, as detailed in Section 6.1.4 of this chapter. Results are shown for the SRES scenarios A1B, A2, B1 and B2, for the seven countries that feature in the FUND case study. Note that there are no SLR impacts for Ethiopia and Zambia, as these are landlocked countries. There are also no estimated storm impacts for Ethiopia or Zambia, because historical storm data from CRED (2018) suggested that storms damages in Sub-Saharan Africa have been overwhelmingly concentrated in South-Eastern countries, such as Madagascar, South Africa, Zimbabwe and Mozambique. Historical storm damages in Ethiopia and Zambia have been negligible in comparison. These countries, thus, were allocated a similarly negligible percentage of the FUND SSA region's storm damages. In contrast, as per historical storm data from CRED (2018), Egypt was allocated 29% of its region's estimated storm damage costs; however, these were so minimal that estimated storm damage repair costs in Egypt were also negligible. Across all countries, one can see that agricultural, water and energy impacts at times dominate those from SLR and storms. There are, however, exceptions to this; for example, the relatively small agricultural impacts estimated for Zambia.

The data in Table 6.1 illustrates why it was desirable for countries from a variety of FUND regions to be included in the case study, as some regions were estimated to experienced far larger relative impacts to sectors than others. For example, demand for energy in Egypt was estimated to be affected by as much as 48.5%, whereas demand for energy in Mexico was never estimated to change by more than 3.5%. Such differences arose because the parameters of FUND's impact functions were calibrated separately for each region based on relevant empirical studies. The correlations of these regional parameter values with the incomes of the regions in 1990 are low[119], ranging from -0.35 to 0.37, as parameter differences reflect differences in climate, geography and economic focus. The calibration coefficient for increased costs from space heating, for example, is nearly nine times larger in FUND for the North African region than for the United States. Such differences would not necessarily have been picked up had the focus solely been on using countries with a range of starting incomes and levels of inequality. In addition, exogenous growth projections in population and income were different in different regions, and these too feature in sector impact functions.

Beyond observing that expenditures on increased coastal protection and repairing storm damages were typically relatively small in comparison to impacts on other sectors, one can see from Table 6.1 that implausibly large, i.e. greater than 100%, decreases in water output were observed for many countries and scenarios. As FUND estimates output changes for the water sector, these overly large impacts do not include any IOA-estimated indirect effects. The implausibility must, thus, stem from problems with (a) the functional form or calibration of the FUND water impact function, (b) the method used in this case-study to disaggregate regional impacts down to a country-level, or (c) errors in the SAMs for, at least, the water sector. The second option appears unlikely, given that implausibly large impacts were also generated for the US, which has its own region in the FUND model, and so did not need to be disaggregated. It also seems unlikely that SAMs for Egypt, the US and Vietnam, all constructed by different researchers, all underestimated the size of the respective water sectors. Moreover, the sizes of the water sectors in the SAMs are consistent with those quoted in input-output tables (IOTs) for the applicable years. For example, according to the multi-region IOT from the Asian Development Bank (ADB, 2007a), the output of the Vietnamese utilities sector in 2007 was 86 trillion Vietnamese Dong, while the SAM used in this case study estimated it to be 84 trillion Vietnamese Dong. In addition, the breakdown of utilities output between water and other utilities in the case study SAM is equivalent to that suggested by other ADB data (ADB, 2007b). This all implies that the most likely source of error is the FUND water impact function itself, which would be consistent with a common criticism of IAMs, as described in Chapters 3 and 7, that their

[119] 1990 incomes were used because these were specified exogenously, whereas all more recent incomes were determined endogenously, so varied across scenarios.

damage functions are out-of-date and often based on expert guesses or extrapolation, rather than data, for higher temperature changes (Prieg and Yumashev, forthcoming). Unfortunately, FUND's water impact function is based on studies from 1995 and 1996 that were not published in journals and can no longer be found online, so one cannot check the logic underpinning the function.

### 6.2.3 Decision to exclude water impacts

For scenario analysis to be useful, as described in Chapter 3, scenarios must be plausible and internally consistent. The data in Table 6.1 raises doubts about the plausibility of FUND's water impact function. Not only are estimated losses greater than 100% in many countries and scenarios, the agriculture and water sectors appear to be constructed independently, without consideration of the consistency of results when agriculture and water are taken together. In Vietnam, for example, despite water resources being completely wiped out, the agricultural sector enjoys sizable increases in output. To generate plausible and internally consistent scenarios, FUND-estimated water impacts were, thus, omitted from the results and analysis in section 6.3 of this chapter. Chapter 8 does, however, use an IOA of the SAMs to estimate impacts from a unit change in water sector output, and then compares these to equivalent results generated for other sectors, to reflect on the possible effects that water sector impacts could have, relative to other sectors, on climate change income inequality effects.

As FUND's impact functions for different sectors are entirely independent from one another, and were constructed using separate analyses of impact studies, the removal of water impacts did not impact on estimates for any other sector, such as agriculture.

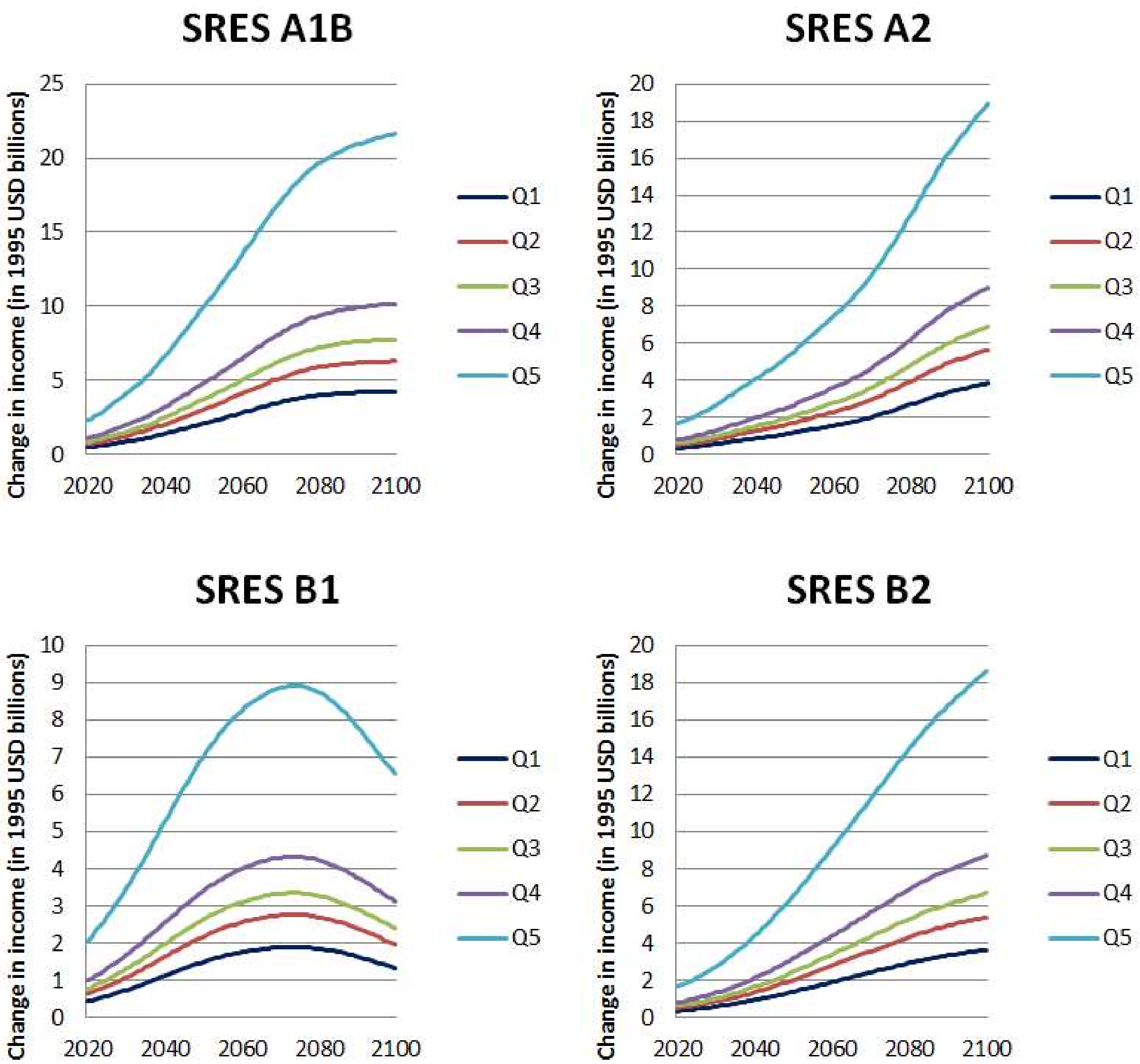
## 6.3 Results

Results are presented for Egypt, Ethiopia, India, Mexico, the US, Vietnam and Zambia, in alphabetical order. Results are aggregated effects from all four sectors, agriculture, energy, SLR and storms. A breakdown of the sector-by-sector contributions to the aggregate results presented in this chapter can be found in Chapter 8.

### 6.3.1 Egypt

As shown in Figure 6.1, cumulative impacts in absolute terms were unequally distributed across household groups, with higher expenditure quintiles experiencing greater deviations in incomes from the baseline, i.e. from the counterfactual world with no economic impacts from climate change. Impacts were positive for all household groups between 2020 and 2100, and continuously increased in all scenarios, except B1, where they rose to a peak around 2073 to 2074, and then fell.

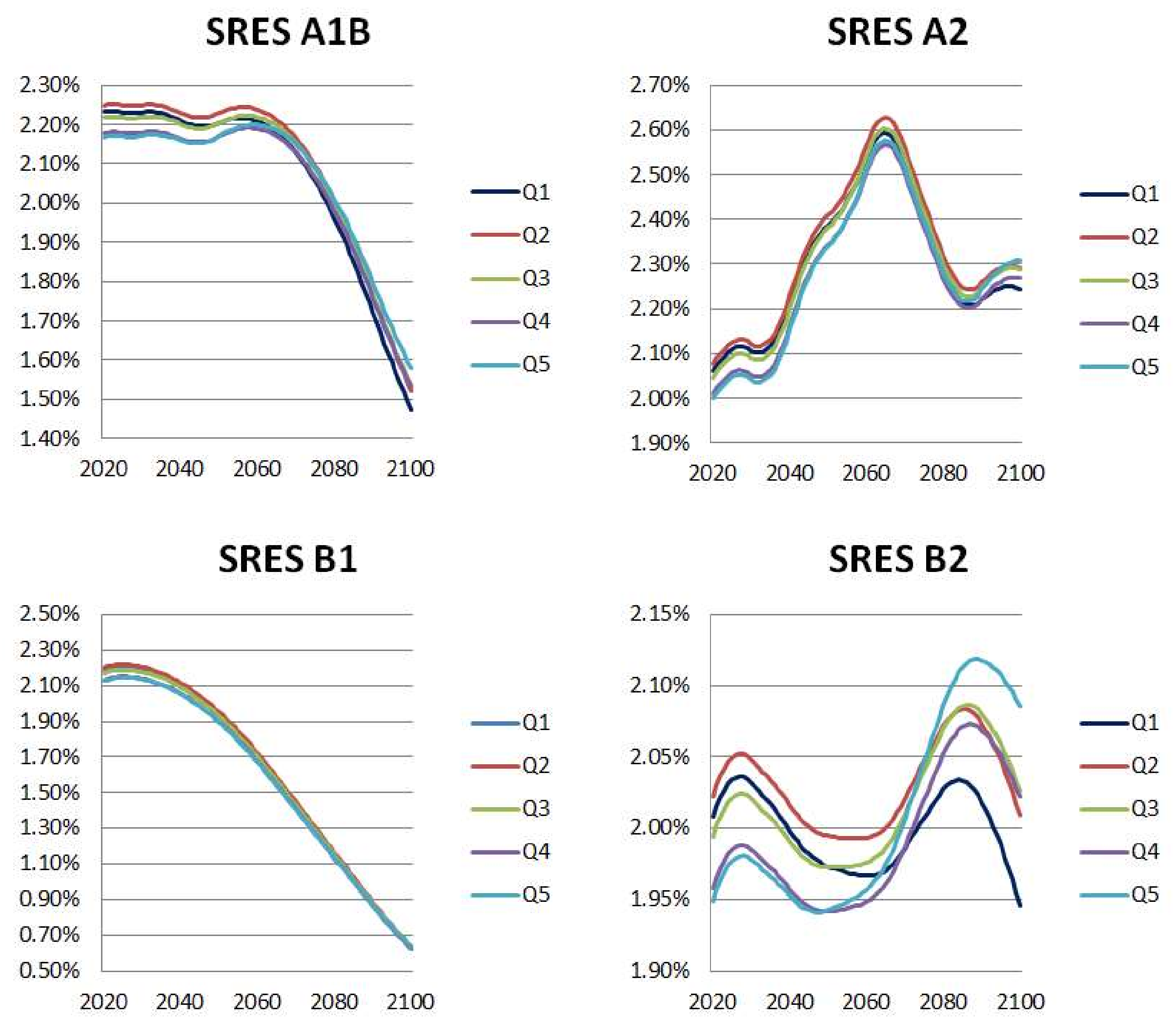
Figure 6.1 – Cumulative changes (in 1995 USD billions) in Egyptian household expenditure quintiles' incomes from counterfactual baseline incomes, in four SRES scenarios




Notes: Figure shows the cumulative changes in income for each Egyptian household expenditure quintile as a result of FUND's estimated climate change impacts on agricultural output, energy expenditure, expenditure building coastal defences and expenditure on reconstruction after storm damages. Results are aggregated direct and indirect effects from all four sectors. The case study was run from 2020 to 2100 for SRES scenarios A1B, A2, B1 and B2. Q1 represents the income of the lowest expenditure quintile, and Q5 represents the income of highest expenditure quintile.

When viewed as percentage changes from baseline incomes, these cumulative impacts did not alter any household group's income by more than 2.64%, at any time, in any scenario. As shown in Figure 6.2, impacts in percentage terms displayed much less variation across different household groups than when viewed in absolute terms, with the maximum difference of proportional impacts across household groups ranging over time from only 0.01 to 0.14 percentage points. The 'impact ranking', i.e. ordering using magnitudes of proportional impacts, of household groups also varied with time.

Figure 6.2 – Cumulative changes in Egyptian household expenditure quintiles' incomes, as percentages of counterfactual baseline incomes, in four SRES scenarios




Notes: Figure shows the cumulative changes in incomes, expressed as percentages of counterfactual baseline incomes, for each Egyptian household expenditure quintile, as a result of FUND's estimated climate change impacts on agricultural output, energy expenditure, expenditure building coastal defences and expenditure on reconstruction after storm damages. Results are aggregated direct and indirect effects from all four sectors. The case study was run from 2020 to 2100 for SRES scenarios A1B, A2, B1 and B2. The counterfactual baseline incomes assume no effects from climate change. Q1 represents the income of the lowest expenditure quintile, and Q5 represents the income of highest expenditure quintile.

The baseline ratios, i.e. the Q5/Q1, Q5/Q3, Q3/Q1 and (Q4+Q5)/(Q1+Q2) ratios in the Egyptian SAM, were 4.78, 2.70, 1.77, and 2.91 respectively. Table 6.2 shows the percentage difference between these ratios and the baseline ratios, e.g. $\left[(Q5/Q1)_t - (\widetilde{Q5}/\widetilde{Q1})\right]/(\widetilde{Q5}/\widetilde{Q1})$, at 2020 and 2100, and the maximum and minimum percentage difference observed during this time period, in the four SRES scenarios. One can see that cumulative climate change impacts reduced inequality at the start of the time period, but increased inequality by the end of the time period. All differences from the baseline were, however, very small when compared to the baseline ratios themselves, with ratio changes ranging between -0.07% and 0.14%.

Table 6.2 – Percentage difference of Egyptian Q5/Q1, Q5/Q3, Q3/Q1 and (Q4+Q5)/(Q1+Q2) ratios from baseline ratios at 2020 and 2100, and maximum and minimum percentage difference observed during this time period, in four SRES scenarios

| Scenario | Ratio | Change at 2020 | Change at 2100 | Maximum change between 2020 and 2100 | Minimum change between 2020 and 2100 |
|---|---|---|---|---|---|
| A1B | Q5/Q1 | -0.06% | 0.10% | 0.10% | -0.06% |
| A1B | Q5/Q3 | -0.05% | 0.04% | 0.04% | -0.05% |
| A1B | Q3/Q1 | -0.01% | 0.06% | 0.06% | -0.01% |
| A1B | (Q4+Q5)/(Q1+Q2) | -0.07% | 0.06% | 0.06% | -0.07% |
| A2 | Q5/Q1 | -0.06% | 0.06% | 0.06% | -0.06% |
| A2 | Q5/Q3 | -0.05% | 0.02% | 0.02% | -0.05% |
| A2 | Q3/Q1 | -0.02% | 0.05% | 0.05% | -0.02% |
| A2 | (Q4+Q5)/(Q1+Q2) | -0.07% | 0.02% | 0.02% | -0.07% |
| B1 | Q5/Q1 | -0.06% | 0.01% | 0.01% | -0.06% |
| B1 | Q5/Q3 | -0.04% | 0.00% | 0.00% | -0.04% |
| B1 | Q3/Q1 | -0.01% | 0.01% | 0.01% | -0.01% |
| B1 | (Q4+Q5)/(Q1+Q2) | -0.06% | 0.00% | 0.00% | -0.06% |
| B2 | Q5/Q1 | -0.06% | 0.14% | 0.14% | -0.06% |
| B2 | Q5/Q3 | -0.04% | 0.06% | 0.06% | -0.04% |
| B2 | Q3/Q1 | -0.01% | 0.08% | 0.08% | -0.01% |
| B2 | (Q4+Q5)/(Q1+Q2) | -0.06% | 0.08% | 0.08% | -0.06% |

Notes: Table shows the percentage difference of Egyptian Q5/Q1, Q5/Q3, Q3/Q1 and (Q4+Q5)/(Q1+Q2) ratios from counterfactual baseline ratios at 2020 and 2100, and the maximum and minimum percentage difference from counterfactual baseline ratios observed during this time period. Q1 represents the income of the lowest expenditure quintile, and Q5 represents the income of highest expenditure quintile. Differences arose as a result of FUND's estimated climate change impacts on agricultural output, energy expenditure, expenditure building coastal defences and expenditure on reconstruction after storm damages. Results are aggregated direct and indirect effects from all four sectors. The case study was run from 2020 to 2100 for SRES scenarios A1B, A2, B1 and B2. The counterfactual baseline incomes assume no effects from climate change.

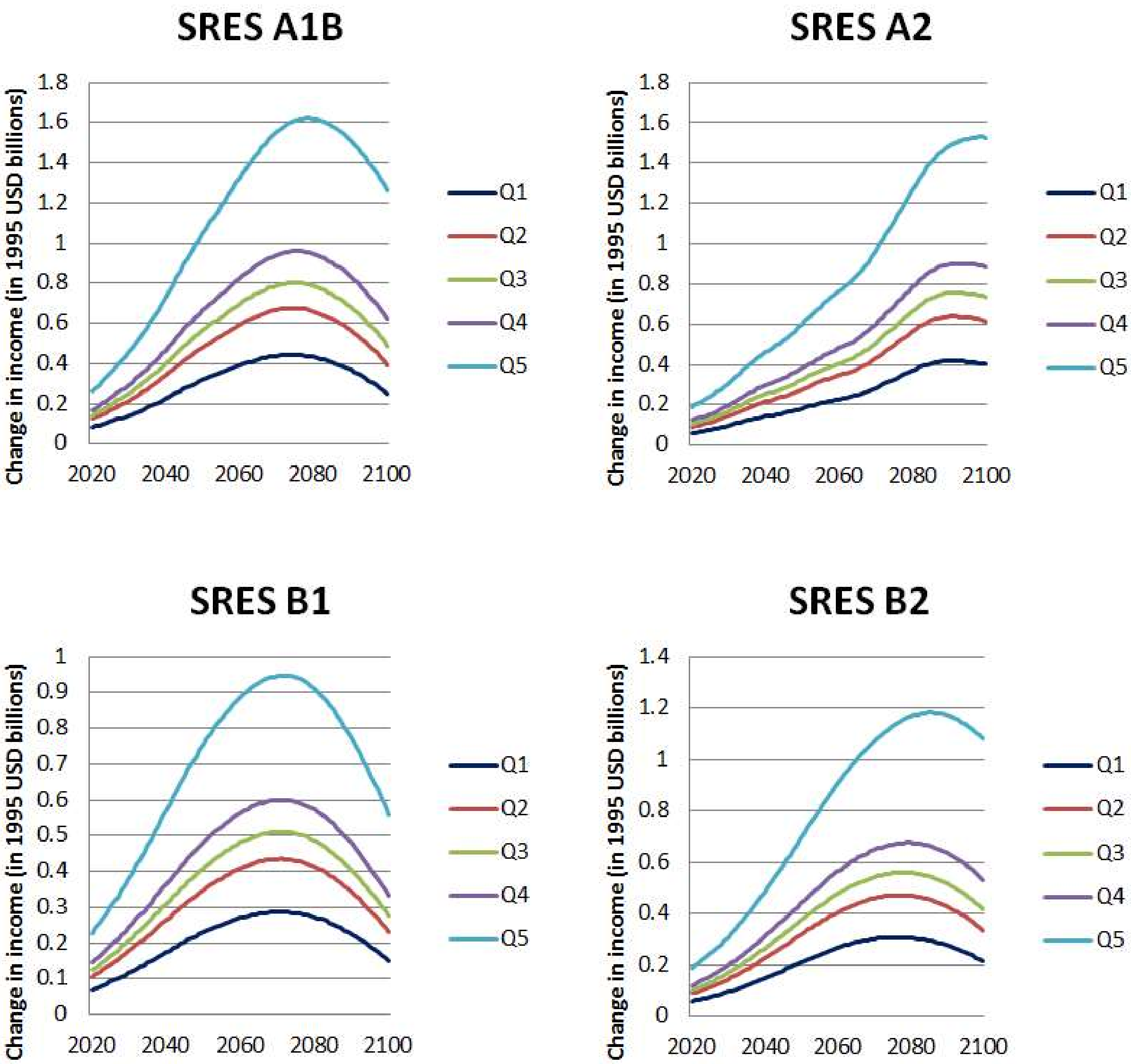
### 6.3.2 Ethiopia

As shown in Figure 6.3, cumulative impacts in absolute terms were unequally distributed across household groups, with higher expenditure quintiles experiencing greater deviations in incomes from the baseline. Impacts were positive for all household groups between 2020 and 2100, and in all scenarios rose to a peak before falling. In A2, however, the peak occurred very close to 2100, and so only a minimal decrease was observed.

When viewed as percentage changes from baseline incomes, these cumulative impacts did not alter any household group's income by more than 2.72%, at any time, in any scenario. As shown in Figure 6.4, greater differences in impacts, in percentage terms, across household groups were observed at the start of the time period in all scenarios, with an initial spread of proportional impacts of approximately 1.2 percentage points. These differences narrowed as time went on, and ultimately became very narrow, i.e. around 0.1 to 0.2 percentage points. The exception was in the A2 scenario, where the spread slightly increased until 2047, before reducing to around 0.6 percentage points in 2100. The impact ranking across household groups remained the same across time and all scenarios, with lower expenditure quintiles seeing proportionately greater impacts.

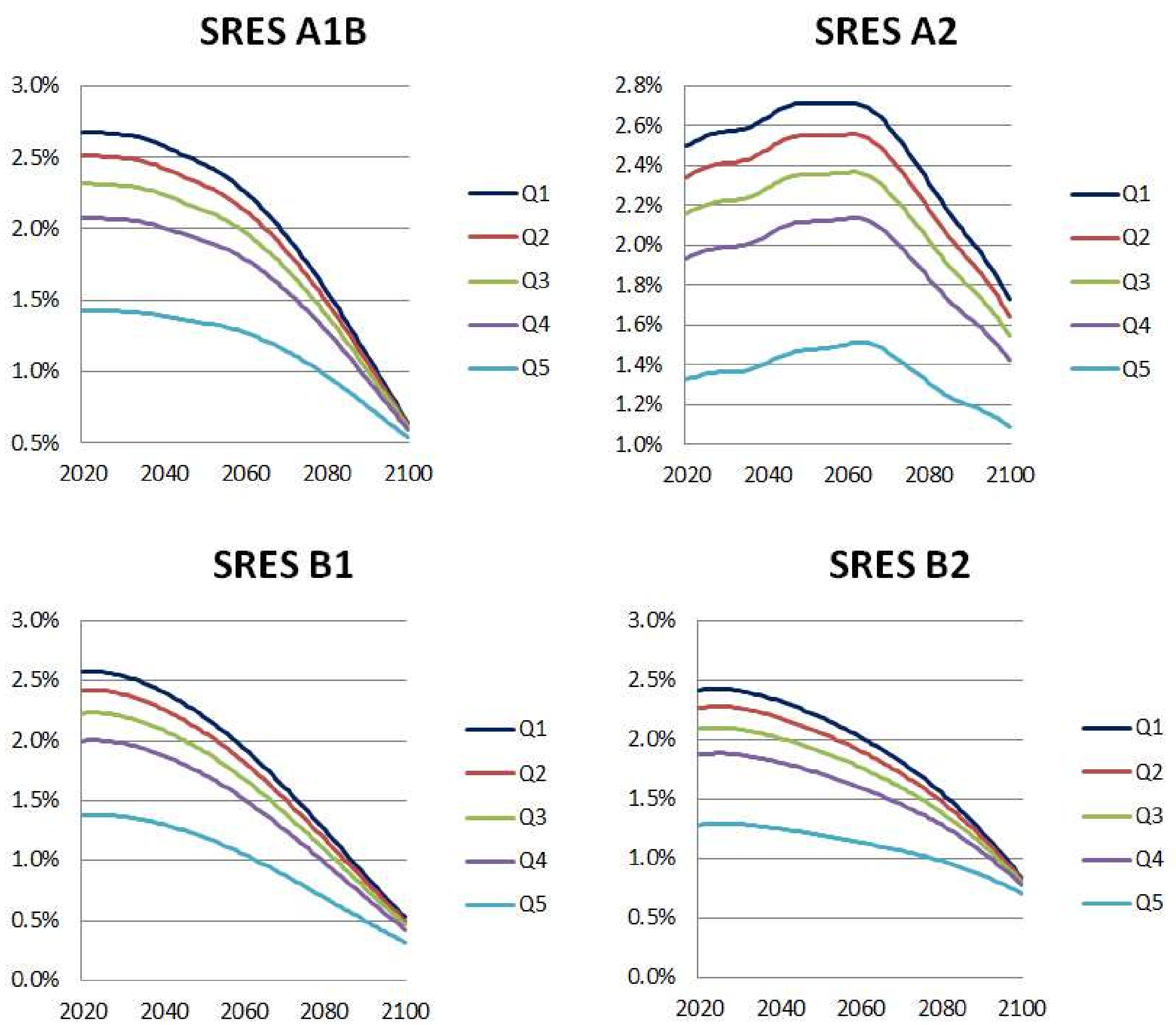
The baseline ratios, i.e. the Q5/Q1, Q5/Q3, Q3/Q1 and (Q4+Q5)/(Q1+Q2) ratios in the Ethiopian SAM, were 6.04, 2.95, 2.05, and 3.33 respectively. Table 6.3 shows the percentage difference between these ratios and the baseline ratios at 2020 and 2100, and the maximum and minimum percentage difference observed during this time period, in each of the four SRES scenarios. One can see that cumulative climate change impacts reduced inequality throughout the time period. Percentage differences from the baseline ratios were larger at the start of the period, but still relatively small. The largest ratio change observed, for example, was a 1.22% decrease in the Q5/Q1 ratio in A1B at 2020. Ratio changes generally decreased as time went on, with the smallest observed being a 0.03% decrease in the Q3/Q1 ratio from the baseline in A1B at 2100. The A2 scenario was an exception, where ratios increased slightly before decreasing.

Figure 6.3 – Cumulative changes (in 1995 USD billions) in Ethiopian household expenditure quintiles' incomes from counterfactual baseline incomes, in four SRES scenarios




Notes: Figure shows the cumulative changes in income for each Ethiopian household expenditure quintile as a result of FUND's estimated climate change impacts on agricultural output and energy expenditure. Results are aggregated direct and indirect effects from both sectors. The case study was run from 2020 to 2100 for SRES scenarios A1B, A2, B1 and B2. Q1 represents the income of the lowest expenditure quintile, and Q5 represents the income of highest expenditure quintile.

Figure 6.4 – Cumulative changes in Ethiopian household expenditure quintiles' incomes, as percentages of counterfactual baseline incomes, in four SRES scenarios




Notes: Figure shows the cumulative changes in incomes, expressed as percentages of counterfactual baseline incomes, for each Ethiopian household expenditure quintile, as a result of FUND's estimated climate change impacts on agricultural output and energy expenditure. Results are aggregated direct and indirect effects from both sectors. The case study was run from 2020 to 2100 for SRES scenarios A1B, A2, B1 and B2. The counterfactual baseline incomes assume no effects from climate change. Q1 represents the income of the lowest expenditure quintile, and Q5 represents the income of highest expenditure quintile.

Table 6.3 – Percentage difference of Ethiopian Q5/Q1, Q5/Q3, Q3/Q1 and (Q4+Q5)/(Q1+Q2) ratios from baseline ratios at 2020 and 2100, and maximum and minimum percentage difference observed during this time period, in four SRES scenarios

| **Scenario** | **Ratio** | **Change at 2020** | **Change at 2100** | **Maximum change between 2020 and 2100** | **Minimum change between 2020 and 2100** |
|---|---|---|---|---|---|
| A1B | Q5/Q1 | -1.22% | -0.10% | -0.10% | -1.22% |
| A1B | Q5/Q3 | -0.87% | -0.07% | -0.07% | -0.87% |
| A1B | Q3/Q1 | -0.35% | -0.03% | -0.03% | -0.35% |
| A1B | (Q4+Q5)/(Q1+Q2) | -0.93% | -0.08% | -0.08% | -0.93% |
| A2 | Q5/Q1 | -1.14% | -0.63% | -0.63% | -1.21% |
| A2 | Q5/Q3 | -0.81% | -0.45% | -0.45% | -0.86% |
| A2 | Q3/Q1 | -0.33% | -0.18% | -0.18% | -0.35% |
| A2 | (Q4+Q5)/(Q1+Q2) | -0.87% | -0.47% | -0.47% | -0.92% |
| B1 | Q5/Q1 | -1.16% | -0.21% | -0.21% | -1.16% |
| B1 | Q5/Q3 | -0.83% | -0.15% | -0.15% | -0.83% |
| B1 | Q3/Q1 | -0.34% | -0.06% | -0.06% | -0.34% |
| B1 | (Q4+Q5)/(Q1+Q2) | -0.89% | -0.16% | -0.16% | -0.89% |
| B2 | Q5/Q1 | -1.10% | -0.13% | -0.13% | -1.10% |
| B2 | Q5/Q3 | -0.79% | -0.09% | -0.09% | -0.79% |
| B2 | Q3/Q1 | -0.32% | -0.04% | -0.04% | -0.32% |
| B2 | (Q4+Q5)/(Q1+Q2) | -0.84% | -0.10% | -0.10% | -0.84% |

Notes: Table shows the percentage difference of Ethiopian Q5/Q1, Q5/Q3, Q3/Q1 and (Q4+Q5)/(Q1+Q2) ratios from counterfactual baseline ratios at 2020 and 2100, and the maximum and minimum percentage difference from counterfactual baseline ratios observed during this time period. Q1 represents the income of the lowest expenditure quintile, and Q5 represents the income of highest expenditure quintile. Differences arose as a result of FUND's estimated climate change impacts on agricultural output and energy expenditure. Results are aggregated direct and indirect effects from both sectors. The case study was run from 2020 to 2100 for SRES scenarios A1B, A2, B1 and B2. The counterfactual baseline incomes assume no effects from climate change.

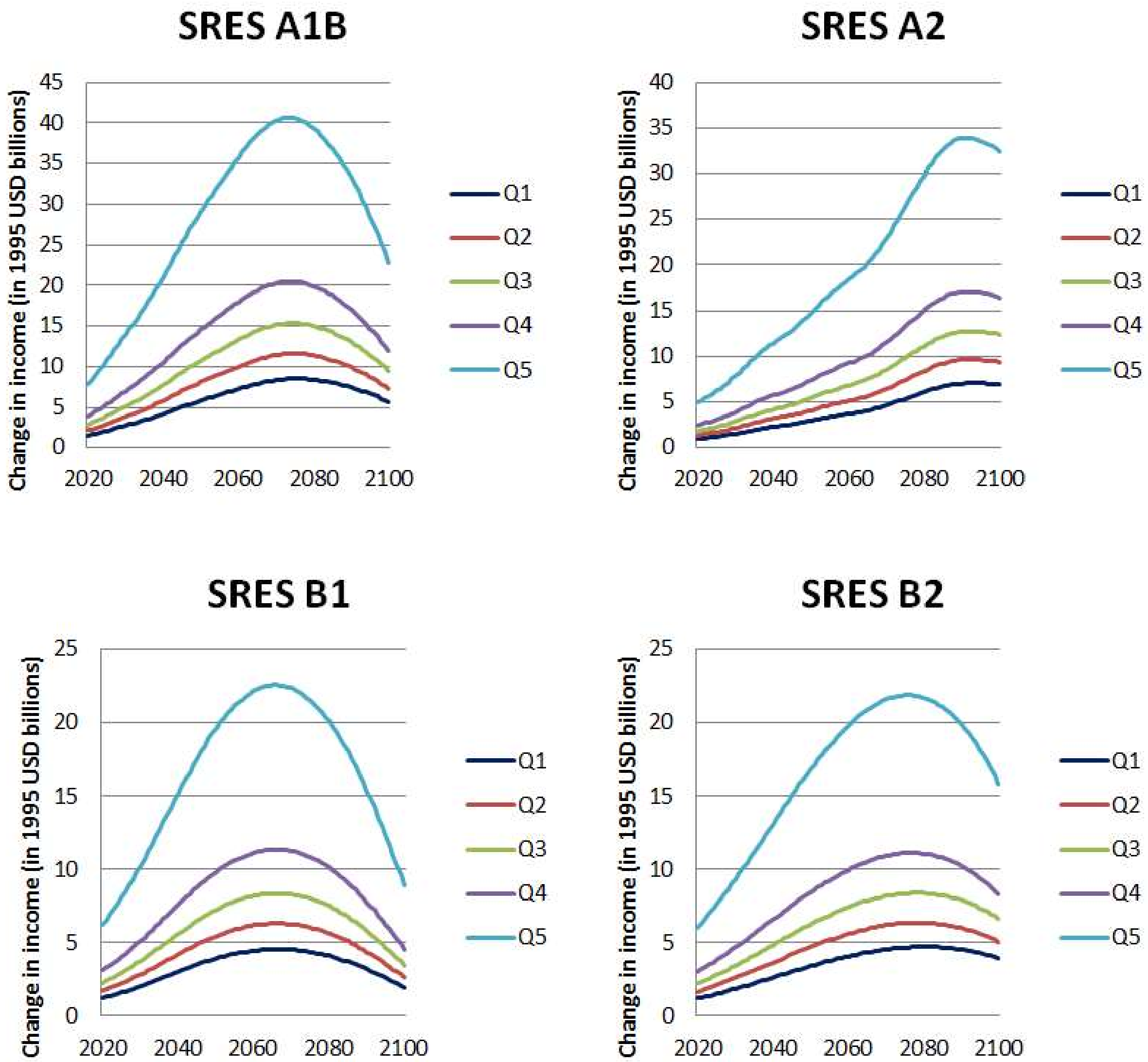
### 6.3.3 India

As shown in Figure 6.5, cumulative impacts in absolute terms were unequally distributed across household groups, with higher expenditure quintiles experiencing greater deviations in incomes from the baseline. Impacts were positive for all household groups between 2020 and 2100, and in all scenarios rose to a peak before falling.

When viewed as percentage changes from baseline incomes, these cumulative impacts did not alter any household group's income by more than 1.3%, at any time, in any scenario. As shown in Figure 6.6, impacts in percentage terms across household groups generally differed by around 0.19 percentage points in 2020. In A1B and B1, the spread gradually narrowed as time progressed to around 0.11 and 0.05 percentage points respectively. Meanwhile, in A2 and B2, the spread first increased to 0.25 and 0.23 percentage points respectively, before decreasing to 0.19 and 0.21 percentage points respectively. The ranking of proportional impacts across household groups remained the same across time and all scenarios, with lower expenditure quintiles seeing proportionately greater impacts.

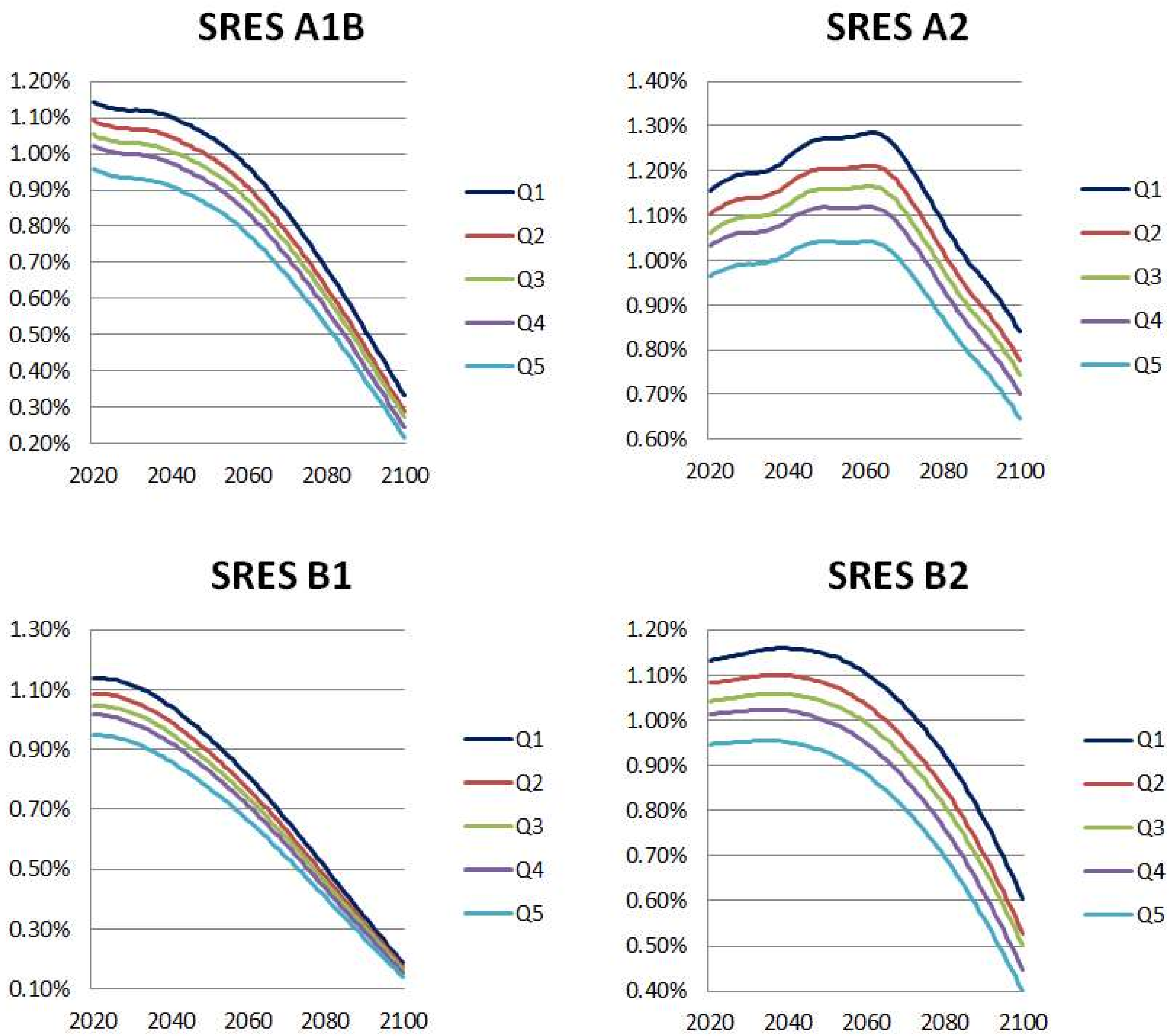
The baseline ratios, i.e. the Q5/Q1, Q5/Q3, Q3/Q1 and (Q4+Q5)/(Q1+Q2) ratios in the Indian SAM, were 6.11, 3.02, 2.03, and 3.63 respectively. Table 6.4 shows the percentage difference between these ratios and the baseline ratios at 2020 and 2100, and the maximum and minimum percentage difference observed during this time period, in the four SRES scenarios. One can see that cumulative climate change impacts reduced inequality throughout the time period. All differences from the baseline were, however, very small when compared to the baseline ratios themselves, with ratio changes ranging from -0.02% to -0.24%.

Figure 6.5 – Cumulative changes (in 1995 USD billions) in Indian household expenditure quintiles' incomes from counterfactual baseline incomes, in four SRES scenarios




Notes: Figure shows the cumulative changes in income for each Indian household expenditure quintile as a result of FUND's estimated climate change impacts on agricultural output, energy expenditure, expenditure building coastal defences and expenditure on reconstruction after storm damages. Results are aggregated direct and indirect effects from all four sectors. The case study was run from 2020 to 2100 for SRES scenarios A1B, A2, B1 and B2. Q1 represents the income of the lowest expenditure quintile, and Q5 represents the income of highest expenditure quintile.

Figure 6.6 – Cumulative changes in Indian household expenditure quintiles' incomes, as percentages of counterfactual baseline incomes, in four SRES scenarios




Notes: Figure shows the cumulative changes in incomes, expressed as percentages of counterfactual baseline incomes, for each Indian household expenditure quintile, as a result of FUND's estimated climate change impacts on agricultural output, energy expenditure, expenditure building coastal defences and expenditure on reconstruction after storm damages. Results are aggregated direct and indirect effects from all four sectors. The case study was run from 2020 to 2100 for SRES scenarios A1B, A2, B1 and B2. The counterfactual baseline incomes assume no effects from climate change. Q1 represents the income of the lowest expenditure quintile, and Q5 represents the income of highest expenditure quintile.

Table 6.4 – Percentage difference of Indian Q5/Q1, Q5/Q3, Q3/Q1 and (Q4+Q5)/(Q1+Q2) ratios from baseline ratios at 2020 and 2100, and maximum and minimum percentage difference observed during this time period, in four SRES scenarios

| **Scenario** | **Ratio** | **Change at 2020** | **Change at 2100** | **Maximum change between 2020 and 2100** | **Minimum change between 2020 and 2100** |
|---|---|---|---|---|---|
| A1B | Q5/Q1 | -0.18% | -0.11% | -0.11% | -0.19% |
| A1B | Q5/Q3 | -0.09% | -0.06% | -0.06% | -0.10% |
| A1B | Q3/Q1 | -0.09% | -0.06% | -0.06% | -0.09% |
| A1B | (Q4+Q5)/(Q1+Q2) | -0.13% | -0.08% | -0.08% | -0.14% |
| A2 | Q5/Q1 | -0.19% | -0.19% | -0.19% | -0.24% |
| A2 | Q5/Q3 | -0.10% | -0.10% | -0.10% | -0.12% |
| A2 | Q3/Q1 | -0.09% | -0.10% | -0.09% | -0.12% |
| A2 | (Q4+Q5)/(Q1+Q2) | -0.14% | -0.14% | -0.14% | -0.17% |
| B1 | Q5/Q1 | -0.19% | -0.05% | -0.05% | -0.19% |
| B1 | Q5/Q3 | -0.10% | -0.02% | -0.02% | -0.10% |
| B1 | Q3/Q1 | -0.09% | -0.02% | -0.02% | -0.09% |
| B1 | (Q4+Q5)/(Q1+Q2) | -0.14% | -0.03% | -0.03% | -0.14% |
| B2 | Q5/Q1 | -0.18% | -0.21% | -0.18% | -0.22% |
| B2 | Q5/Q3 | -0.10% | -0.10% | -0.10% | -0.11% |
| B2 | Q3/Q1 | -0.09% | -0.10% | -0.09% | -0.11% |
| B2 | (Q4+Q5)/(Q1+Q2) | -0.13% | -0.14% | -0.13% | -0.16% |

Notes: Table shows the percentage difference of Indian Q5/Q1, Q5/Q3, Q3/Q1 and (Q4+Q5)/(Q1+Q2) ratios from counterfactual baseline ratios at 2020 and 2100, and the maximum and minimum percentage difference from counterfactual baseline ratios observed during this time period. Q1 represents the income of the lowest expenditure quintile, and Q5 represents the income of highest expenditure quintile. Differences arose as a result of FUND's estimated climate change impacts on agricultural output, energy expenditure, expenditure building coastal defences and expenditure on reconstruction after storm damages. Results are aggregated direct and indirect effects from all four sectors. The case study was run from 2020 to 2100 for SRES scenarios A1B, A2, B1 and B2. The counterfactual baseline incomes assume no effects from climate change.

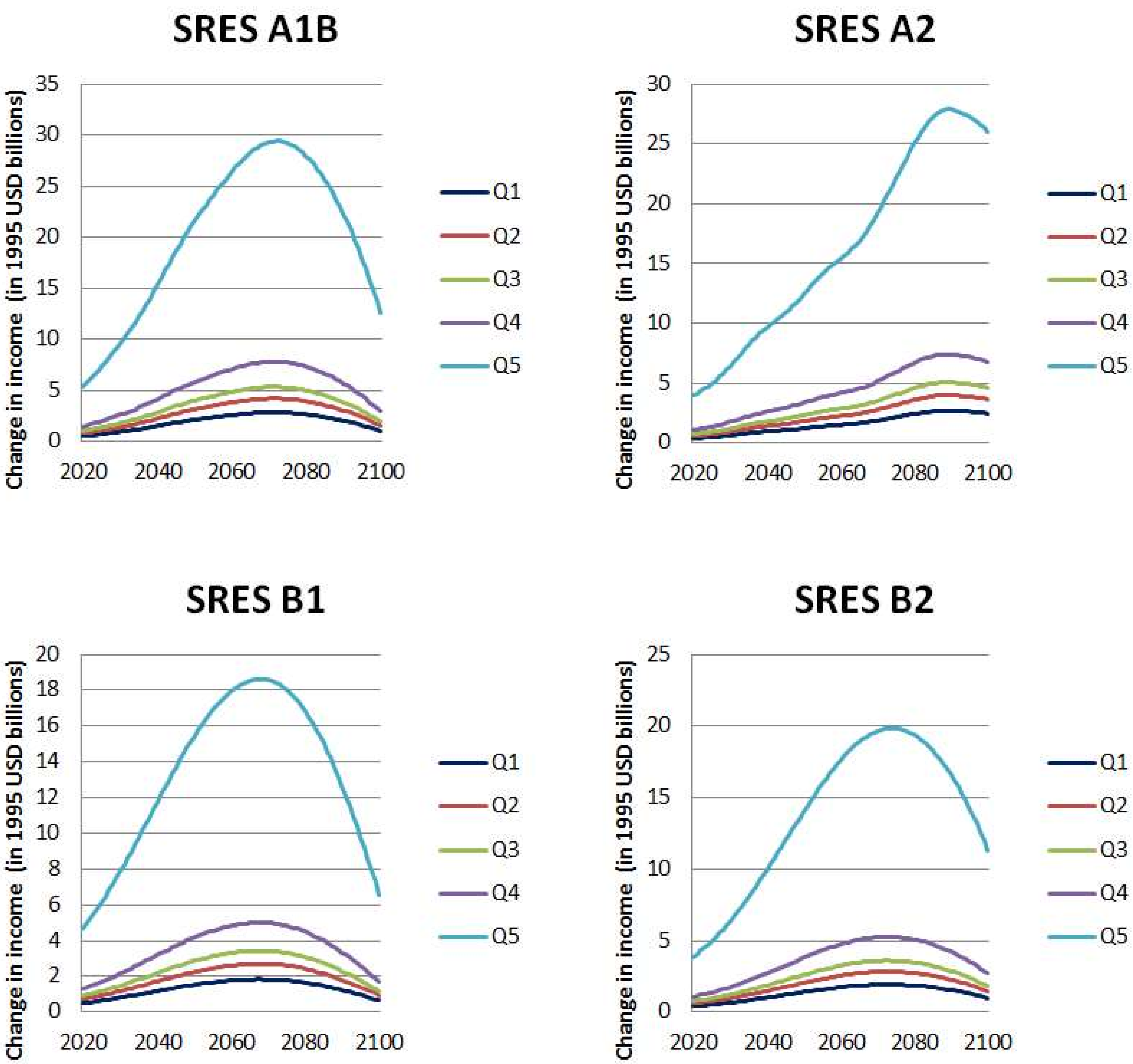
### 6.3.4 Mexico

As shown in Figure 6.7, cumulative impacts in absolute terms were unequally distributed across household groups, with higher income quintiles experiencing greater deviations in incomes from the baseline. Impacts were positive for all household groups between 2020 and 2100, and in all scenarios rose to a peak before falling.

When viewed as percentage changes from baseline incomes, these cumulative impacts did not alter any household group's income by more than 0.78%, at any time, in any scenario. As shown in Figure 6.8, greater differences of impacts in percentage terms across household groups were observed at 2020 than at 2100, with the spread starting off around 0.12 to 0.13 percentage points in all scenarios, increasing slightly, and narrowing to 0.04, 0.07, 0.03 and 0.05 percentage points in A1B, A2, B1 and B2 respectively. Overall, the spread varied between 0.02 and 0.16 percentage points. The ranking of proportional impacts across household groups remained the same across time and all scenarios, with higher income quintiles seeing proportionately greater impacts.

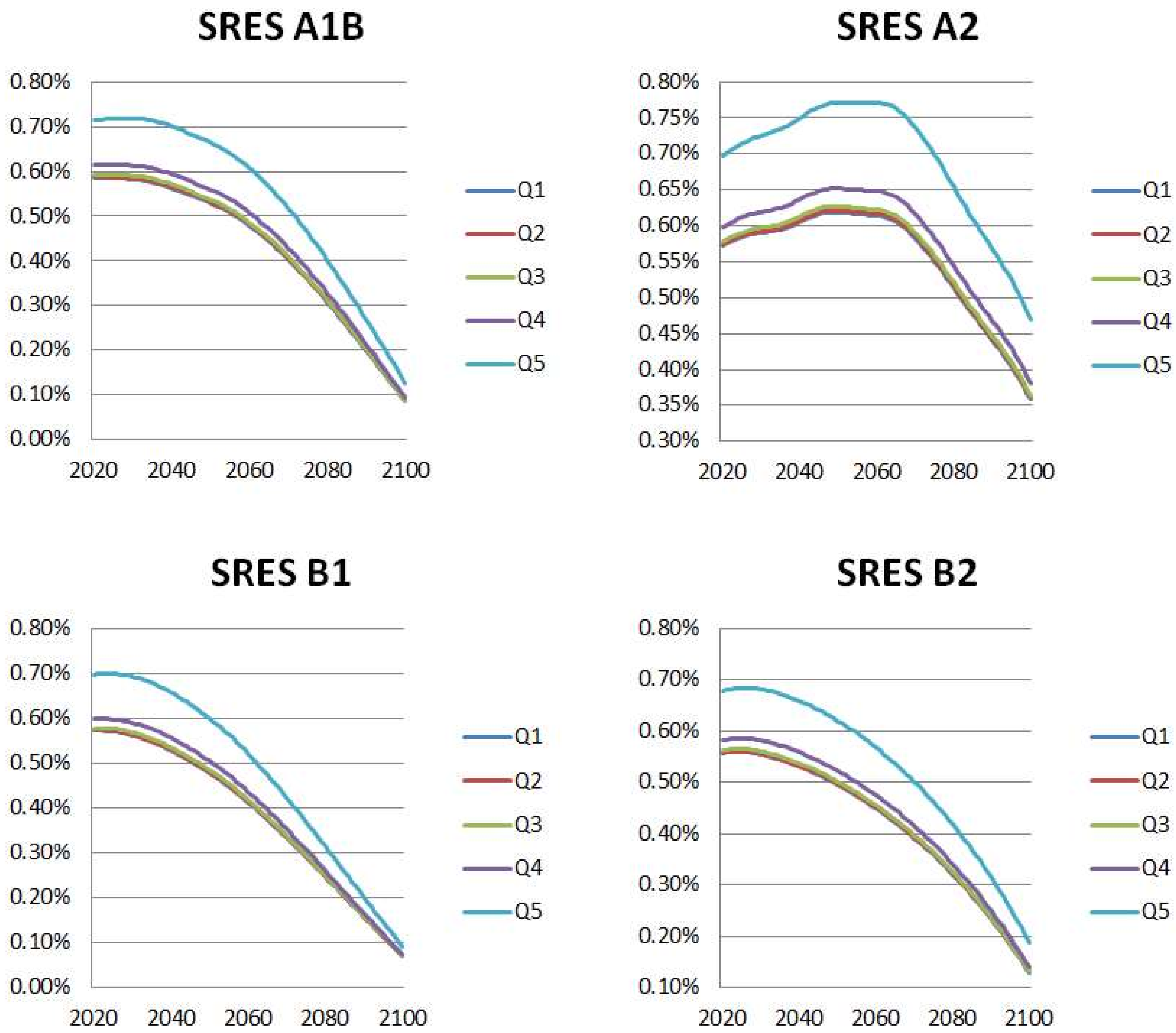
The baseline ratios, i.e. Q5/Q1, Q5/Q3, Q3/Q1 and (Q4+Q5)/(Q1+Q2) in the Mexican SAM, were 8.05, 4.35, 1.85, and 4.30 respectively. Table 6.5 shows the percentage difference between these ratios and the baseline ratios at 2020 and 2100, and the maximum and minimum percentage difference observed during this time period, in the four SRES scenarios. One can see that cumulative climate change impacts increased inequality throughout the time period. All differences from the baseline were, however, very small when compared to the baseline ratios themselves, with ratio changes varying between 0% and 0.16%.

Figure 6.7 – Cumulative changes (in 1995 USD billions) in Mexican household income quintiles' incomes from counterfactual baseline incomes, in four SRES scenarios




Notes: Figure shows the cumulative changes in income for each Mexican household income quintile as a result of FUND's estimated climate change impacts on agricultural output, energy expenditure, expenditure building coastal defences and expenditure on reconstruction after storm damages. Results are aggregated direct and indirect effects from all four sectors. The case study was run from 2020 to 2100 for SRES scenarios A1B, A2, B1 and B2. Q1 represents the income of the lowest income quintile, and Q5 represents the income of highest income quintile.

Figure 6.8 – Cumulative changes in Mexican household income quintiles' incomes, as percentages of counterfactual baseline incomes, in four SRES scenarios




Notes: Figure shows the cumulative changes in incomes, expressed as percentages of counterfactual baseline incomes, for each Mexican household income quintile, as a result of FUND's estimated climate change impacts on agricultural output, energy expenditure, expenditure building coastal defences and expenditure on reconstruction after storm damages. Results are aggregated direct and indirect effects from all four sectors. The case study was run from 2020 to 2100 for SRES scenarios A1B, A2, B1 and B2. The counterfactual baseline incomes assume no effects from climate change. Q1 represents the income of the lowest income quintile, and Q5 represents the income of highest income quintile.

Table 6.5 – Percentage difference of Mexican Q5/Q1, Q5/Q3, Q3/Q1 and (Q4+Q5)/(Q1+Q2) ratios from baseline ratios at 2020 and 2100, and maximum and minimum percentage difference observed during this time period, in four SRES scenarios

| **Scenario** | **Ratio** | **Change at 2020** | **Change at 2100** | **Maximum change between 2020 and 2100** | **Minimum change between 2020 and 2100** |
|---|---|---|---|---|---|
| A1B | Q5/Q1 | 0.13% | 0.04% | 0.14% | 0.04% |
| A1B | Q5/Q3 | 0.12% | 0.04% | 0.13% | 0.04% |
| A1B | Q3/Q1 | 0.01% | 0.00% | 0.01% | 0.00% |
| A1B | (Q4+Q5)/(Q1+Q2) | 0.10% | 0.03% | 0.11% | 0.03% |
| A2 | Q5/Q1 | 0.12% | 0.11% | 0.16% | 0.11% |
| A2 | Q5/Q3 | 0.12% | 0.11% | 0.15% | 0.11% |
| A2 | Q3/Q1 | 0.01% | 0.01% | 0.01% | 0.01% |
| A2 | (Q4+Q5)/(Q1+Q2) | 0.10% | 0.09% | 0.13% | 0.09% |
| B1 | Q5/Q1 | 0.12% | 0.02% | 0.13% | 0.02% |
| B1 | Q5/Q3 | 0.12% | 0.02% | 0.12% | 0.02% |
| B1 | Q3/Q1 | 0.01% | 0.00% | 0.01% | 0.00% |
| B1 | (Q4+Q5)/(Q1+Q2) | 0.10% | 0.02% | 0.10% | 0.02% |
| B2 | Q5/Q1 | 0.12% | 0.06% | 0.13% | 0.06% |
| B2 | Q5/Q3 | 0.11% | 0.06% | 0.12% | 0.06% |
| B2 | Q3/Q1 | 0.00% | 0.00% | 0.01% | 0.00% |
| B2 | (Q4+Q5)/(Q1+Q2) | 0.10% | 0.05% | 0.10% | 0.05% |

Notes: Table shows the percentage difference of Mexican Q5/Q1, Q5/Q3, Q3/Q1 and (Q4+Q5)/(Q1+Q2) ratios from counterfactual baseline ratios at 2020 and 2100, and the maximum and minimum percentage difference from counterfactual baseline ratios observed during this time period. Q1 represents the income of the lowest income quintile, and Q5 represents the income of highest income quintile. Differences arose as a result of FUND's estimated climate change impacts on agricultural output, energy expenditure, expenditure building coastal defences and expenditure on reconstruction after storm damages. Results are aggregated direct and indirect effects from all four sectors. The case study was run from 2020 to 2100 for SRES scenarios A1B, A2, B1 and B2. The counterfactual baseline incomes assume no effects from climate change.

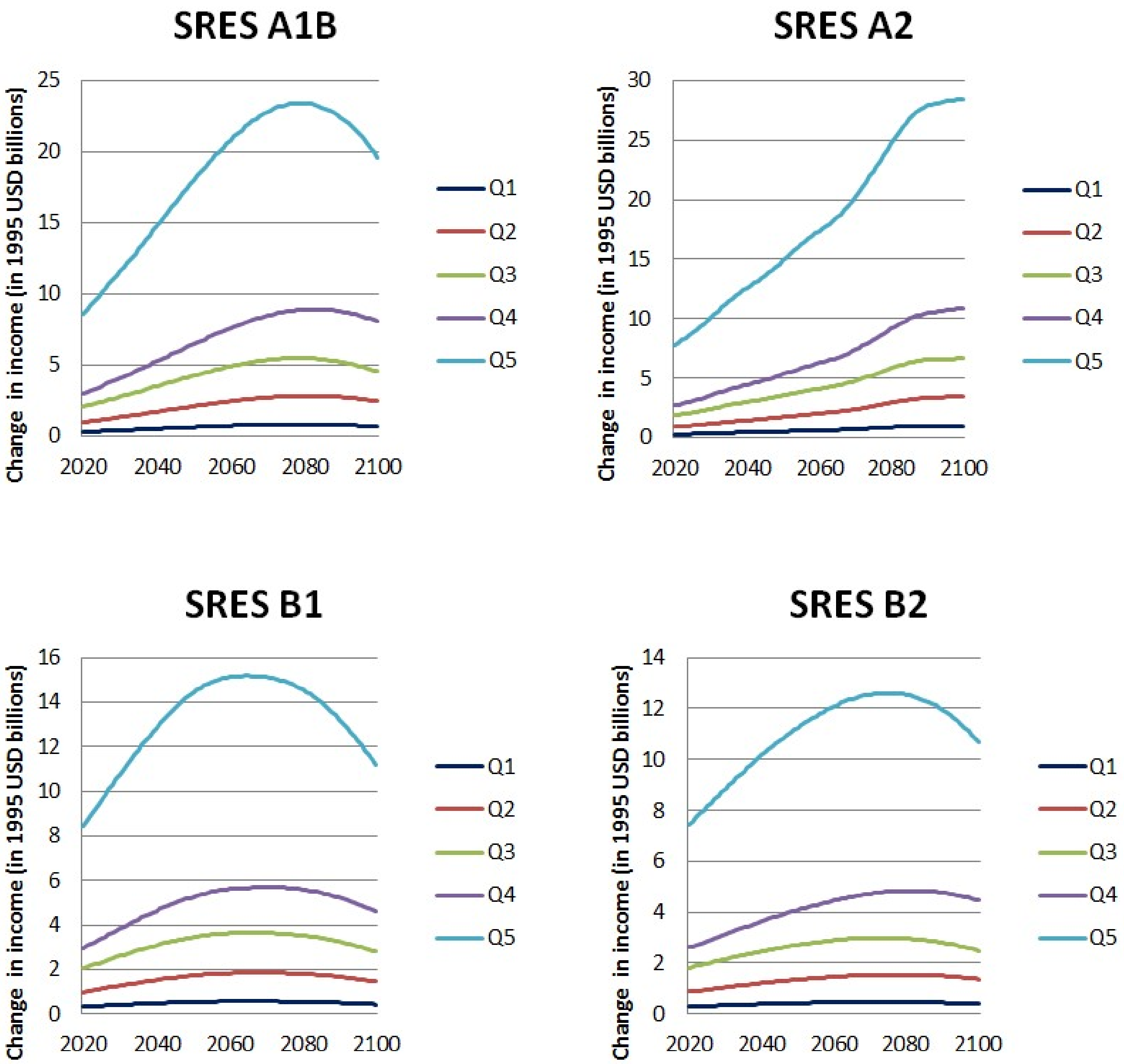
### 6.3.5 United States

As shown in Figure 6.9, cumulative impacts in absolute terms were unequally distributed across household groups, with higher income quintiles experiencing greater deviations in incomes from the baseline. Impacts were positive for all household groups between 2020 and 2100, and in all scenarios, except A2, rose to a peak before falling. In A2, impacts for all household groups continuously rose.

When viewed as percentage changes from baseline incomes, these cumulative impacts did not alter any household group's income by more than 0.17%, at any time, in any scenario. As shown in Figure 6.10, differences in impacts in percentage terms between household groups started off at around 0.06 percentage points at 2020. The spreads then increased slightly until peaking at around 2051, 2067, 2046 and 2056 for A1B, A2, B1 and B2 respectively, before decreasing and ending the time period at 0.04, 0.07, 0.03, and 0.05 percentage points respectively. Overall the spread of percentage impacts across household groups ranged from 0.03 to 0.08 percentage points. The ranking of proportional impacts across most household groups remained the same across time and all scenarios, with higher income quintiles seeing proportionately greater impacts. The third and fourth income quintiles were exceptions, as proportional impacts in all scenarios started off more heavily skewed towards the third quintile; however, as time progressed, proportional impacts on the fourth quintile grew to exceed those on the third.

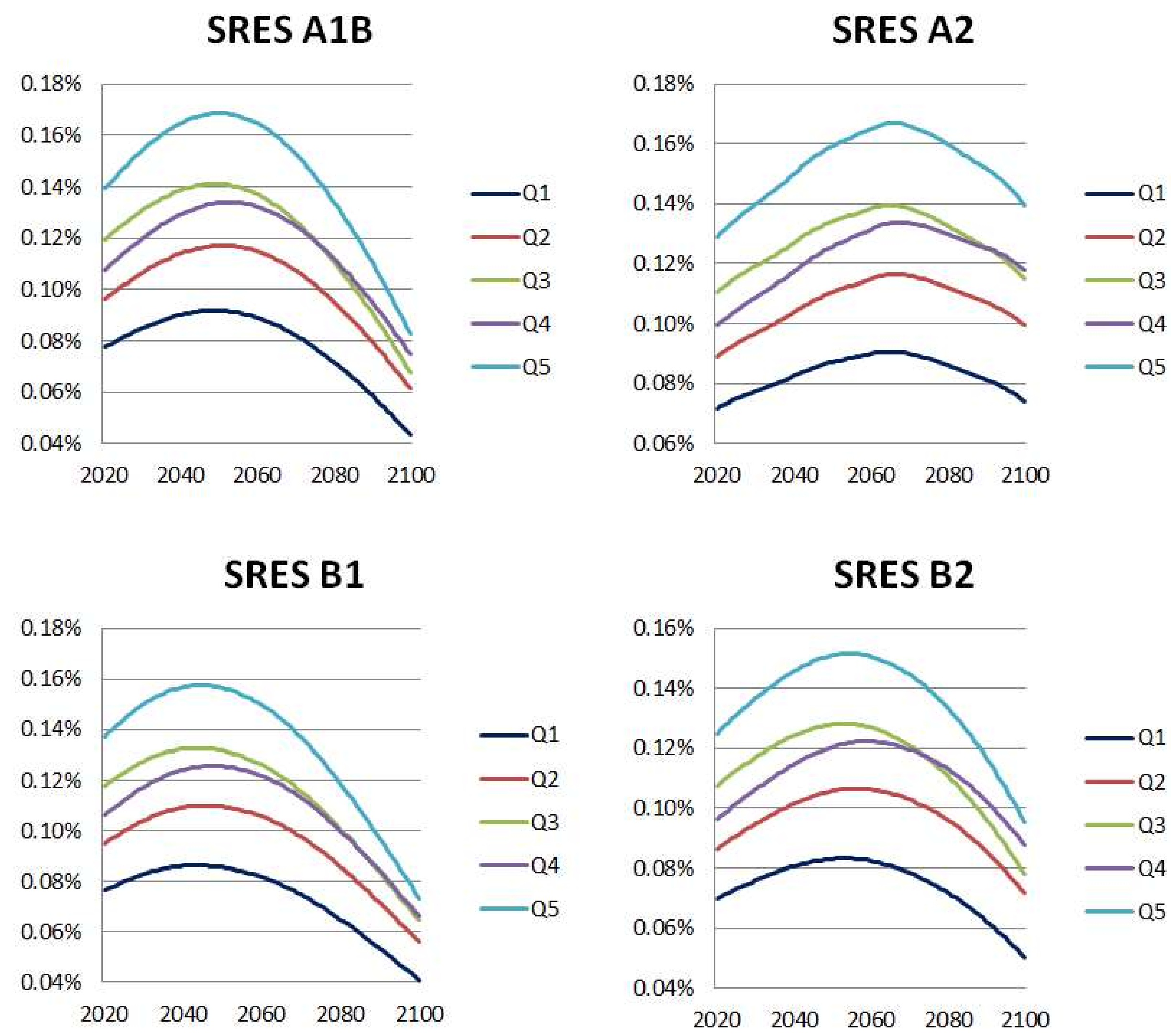
The baseline Q5/Q1, Q5/Q3, Q3/Q1 and (Q4+Q5)/(Q1+Q2) ratios in the US SAM were 14.67, 3.51, 4.18, and 6.07 respectively. Table 6.6 shows the percentage difference between the ratios after climate change impacts and the baseline ratios at 2020 and 2100, and the maximum and minimum percentage difference observed during this time period, in the four SRES scenarios. One can see that cumulative climate change impacts increased inequality throughout the time period. All differences from the baseline were, however, very small when compared to the baseline ratios themselves, with ratio changes ranging from 0.01% to 0.08%.

Figure 6.9 – Cumulative changes (in 1995 USD billions) in American household income quintiles' incomes from counterfactual baseline incomes, in four SRES scenarios




Notes: Figure shows the cumulative changes in income for each American household income quintile as a result of FUND's estimated climate change impacts on agricultural output, energy expenditure, expenditure building coastal defences and expenditure on reconstruction after storm damages. Results are aggregated direct and indirect effects from all four sectors. The case study was run from 2020 to 2100 for SRES scenarios A1B, A2, B1 and B2. Q1 represents the income of the lowest income quintile, and Q5 represents the income of highest income quintile.

Figure 6.10 – Cumulative changes in American household income quintiles' incomes, as percentages of counterfactual baseline incomes, in four SRES scenarios




Notes: Figure shows the cumulative changes in incomes, expressed as percentages of counterfactual baseline incomes, for each American household income quintile, as a result of FUND's estimated climate change impacts on agricultural output, energy expenditure, expenditure building coastal defences and expenditure on reconstruction after storm damages. Results are aggregated direct and indirect effects from all four sectors. The case study was run from 2020 to 2100 for SRES scenarios A1B, A2, B1 and B2. The counterfactual baseline incomes assume no effects from climate change. Q1 represents the income of the lowest income quintile, and Q5 represents the income of highest income quintile.

Table 6.6 – Percentage difference of American Q5/Q1, Q5/Q3, Q3/Q1 and (Q4+Q5)/(Q1+Q2) ratios from baseline ratios at 2020 and 2100, and maximum and minimum percentage difference observed during this time period, in four SRES scenarios

| **Scenario** | **Ratio** | **Change at 2020** | **Change at 2100** | **Maximum change between 2020 and 2100** | **Minimum change between 2020 and 2100** |
|---|---|---|---|---|---|
| A1B | Q5/Q1 | 0.06% | 0.04% | 0.08% | 0.04% |
| A1B | Q5/Q3 | 0.02% | 0.01% | 0.03% | 0.01% |
| A1B | Q3/Q1 | 0.04% | 0.02% | 0.05% | 0.02% |
| A1B | (Q4+Q5)/(Q1+Q2) | 0.04% | 0.02% | 0.05% | 0.02% |
| A2 | Q5/Q1 | 0.06% | 0.07% | 0.08% | 0.06% |
| A2 | Q5/Q3 | 0.02% | 0.02% | 0.03% | 0.02% |
| A2 | Q3/Q1 | 0.04% | 0.04% | 0.05% | 0.04% |
| A2 | (Q4+Q5)/(Q1+Q2) | 0.04% | 0.04% | 0.05% | 0.04% |
| B1 | Q5/Q1 | 0.06% | 0.03% | 0.07% | 0.03% |
| B1 | Q5/Q3 | 0.02% | 0.01% | 0.02% | 0.01% |
| B1 | Q3/Q1 | 0.04% | 0.02% | 0.05% | 0.02% |
| B1 | (Q4+Q5)/(Q1+Q2) | 0.04% | 0.02% | 0.04% | 0.02% |
| B2 | Q5/Q1 | 0.06% | 0.05% | 0.07% | 0.05% |
| B2 | Q5/Q3 | 0.02% | 0.02% | 0.02% | 0.02% |
| B2 | Q3/Q1 | 0.04% | 0.03% | 0.04% | 0.03% |
| B2 | (Q4+Q5)/(Q1+Q2) | 0.03% | 0.03% | 0.04% | 0.03% |

Notes: Table shows the percentage difference of American Q5/Q1, Q5/Q3, Q3/Q1 and (Q4+Q5)/(Q1+Q2) ratios from counterfactual baseline ratios at 2020 and 2100, and the maximum and minimum percentage difference from counterfactual baseline ratios observed during this time period. Q1 represents the income of the lowest income quintile, and Q5 represents the income of highest income quintile. Differences arose as a result of FUND's estimated climate change impacts on agricultural output, energy expenditure, expenditure building coastal defences and expenditure on reconstruction after storm damages. Results are aggregated direct and indirect effects from all four sectors. The case study was run from 2020 to 2100 for SRES scenarios A1B, A2, B1 and B2. The counterfactual baseline incomes assume no effects from climate change.

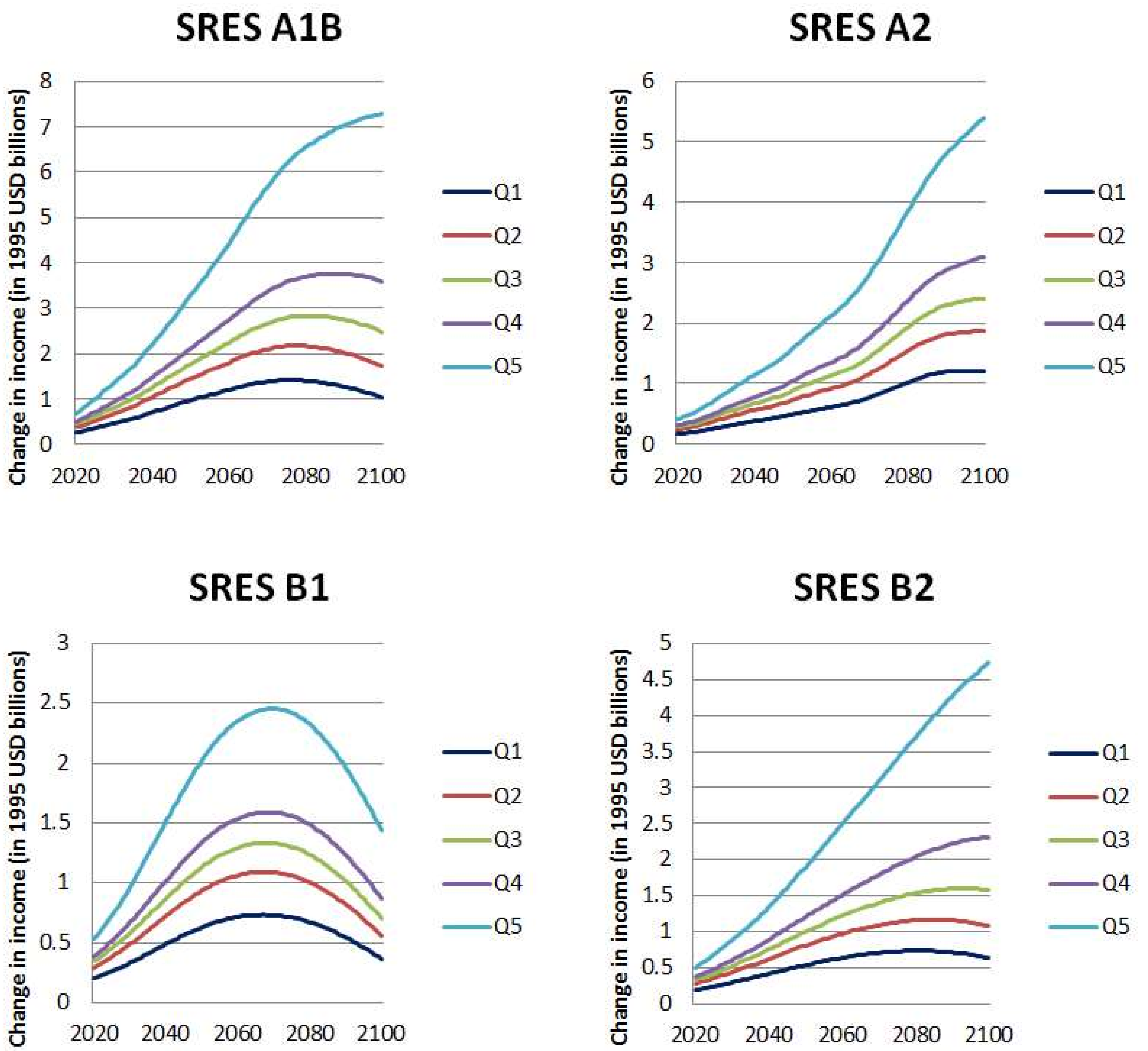
### 6.3.6 Vietnam

As shown in Figure 6.11, cumulative impacts in absolute terms were unequally distributed across household groups, with higher expenditure quintiles experiencing greater deviations in incomes from the baseline. Impacts were positive for all household groups between 2020 and 2100. In B1, all household groups experienced impacts that rose to a peak around 2067 to 2069, before falling. In A1B, all household groups, except the highest expenditure quintile, saw impacts rise to a peak between 2076 and 2088, before impacts started to decrease. Meanwhile, impacts for the highest expenditure quintile continuously rose throughout the 2020 to 2100 time period. In A2, impacts for the two lowest expenditure quintiles rose to a peak just before the end of the time period, while for all other income quintiles, impacts continuously increased. Finally, the three lowest expenditure quintiles in B2 saw impacts rise until around 2081 to 2093, before starting to diminish, while impacts for the two highest expenditure quintiles continuously increased.

When viewed as percentage changes from baseline incomes, these cumulative impacts did not alter any household group's income by more than 4.24%, at any time, in any scenario. As shown in Figure 6.12, impacts in percentage terms in all scenarios started out more dispersed across household groups at the start of the time period, and became more concentrated towards 2100; although in A1B and B2, they started to slightly disperse again towards the very end of the time period. Specifically, the spread of proportional impacts across household groups in 2020 was between 2.28 and 2.42 percentage points. In A1B and B2, these spreads reduced to around 0.03 to 0.04 percentage points, before slightly rising again. In A2 and B1, spreads gradually decreased over time to 0.92 and 0.29 percentage points respectively in 2100.The ranking of proportional impacts across household groups remained the same across time in A2 and B1, with lower expenditure quintiles seeing proportionately greater impacts. This was the initial pattern in A1B and B2; however, as dispersion of proportional impacts across household groups contracted and then expanded again, with the latter the trend was reversed, i.e. higher expenditure quintiles saw proportionately greater impacts.

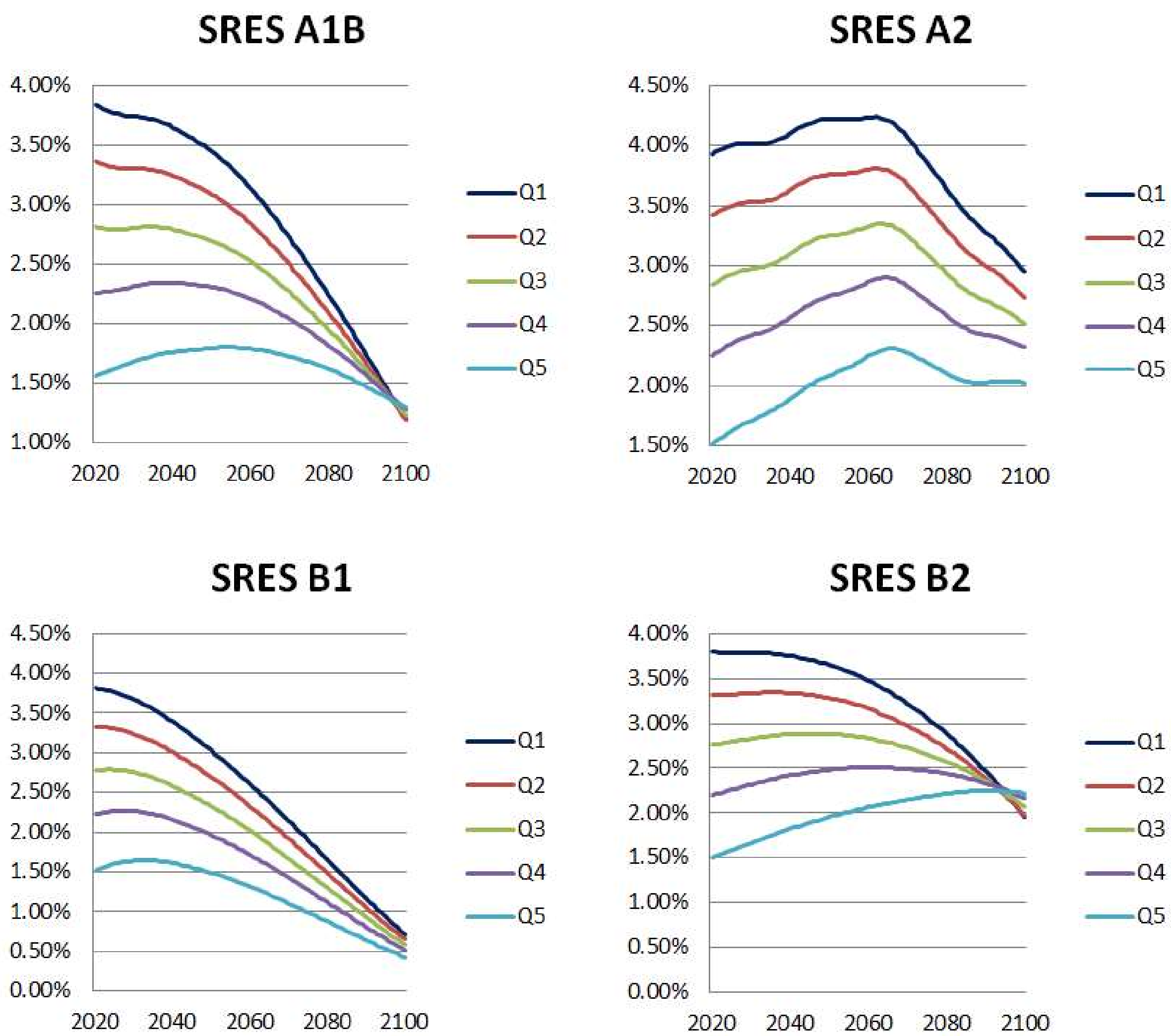
The baseline ratios, i.e. the Q5/Q1, Q5/Q3, Q3/Q1 and (Q4+Q5)/(Q1+Q2) ratios in the Vietnam SAM, were 6.50, 2.79, 2.33, and 3.66 respectively. Table 6.7 shows the percentage difference between these ratios after climate change impacts and the baseline ratios at 2020 and 2100, and the maximum and minimum percentage difference observed during this time period, in the four SRES scenarios. At the start of the time period, one can see that cumulative climate change impacts reduced inequality in all scenarios. This remained true throughout the time period in A2 and B1. In A1B and B2, however, cumulative climate change impacts started to increase inequality by the end of the time period. The largest ratio percentage change observed was a decrease of 2.33% at 2020 in the Q5/Q1 ratio from the baseline in A2. Percentage changes in ratios at the end of the time period were smaller across all scenarios and ratios.

Figure 6.11 – Cumulative changes (in 1995 USD billions) in Vietnamese household expenditure quintiles' incomes from counterfactual baseline incomes, in four SRES scenarios




Notes: Figure shows the cumulative changes in income for each Vietnamese household expenditure quintile as a result of FUND's estimated climate change impacts on agricultural output, energy expenditure, expenditure building coastal defences and expenditure on reconstruction after storm damages. Results are aggregated direct and indirect effects from all four sectors. The case study was run from 2020 to 2100 for SRES scenarios A1B, A2, B1 and B2. Q1 represents the income of the lowest expenditure quintile, and Q5 represents the income of highest expenditure quintile.

Figure 6.12 – Cumulative changes in Vietnamese household expenditure quintiles' incomes, as percentages of counterfactual baseline incomes, in four SRES scenarios




Notes: Figure shows the cumulative changes in incomes, expressed as percentages of counterfactual baseline incomes, for each Vietnamese household expenditure quintile, as a result of FUND's estimated climate change impacts on agricultural output, energy expenditure, expenditure building coastal defences and expenditure on reconstruction after storm damages. Results are aggregated direct and indirect effects from all four sectors. The case study was run from 2020 to 2100 for SRES scenarios A1B, A2, B1 and B2. The counterfactual baseline incomes assume no effects from climate change. Q1 represents the income of the lowest expenditure quintile, and Q5 represents the income of highest expenditure quintile.

Table 6.7 – Percentage difference of Vietnamese Q5/Q1, Q5/Q3, Q3/Q1 and (Q4+Q5)/(Q1+Q2) ratios from baseline ratios at 2020 and 2100, and maximum and minimum percentage difference observed during this time period, in four SRES scenarios

| **Scenario** | **Ratio** | **Change at 2020** | **Change at 2100** | **Maximum change between 2020 and 2100** | **Minimum change between 2020 and 2100** |
|---|---|---|---|---|---|
| A1B | Q5/Q1 | -2.20% | 0.10% | 0.10% | -2.20% |
| A1B | Q5/Q3 | -1.22% | 0.06% | 0.06% | -1.22% |
| A1B | Q3/Q1 | -0.99% | 0.04% | 0.04% | -0.99% |
| A1B | (Q4+Q5)/(Q1+Q2) | -1.69% | 0.10% | 0.10% | -1.69% |
| A2 | Q5/Q1 | -2.33% | -0.89% | -0.89% | -2.33% |
| A2 | Q5/Q3 | -1.29% | -0.48% | -0.48% | -1.29% |
| A2 | Q3/Q1 | -1.05% | -0.41% | -0.41% | -1.05% |
| A2 | (Q4+Q5)/(Q1+Q2) | -1.79% | -0.67% | -0.67% | -1.79% |
| B1 | Q5/Q1 | -2.20% | -0.28% | -0.28% | -2.20% |
| B1 | Q5/Q3 | -1.22% | -0.16% | -0.16% | -1.22% |
| B1 | Q3/Q1 | -0.99% | -0.13% | -0.13% | -0.99% |
| B1 | (Q4+Q5)/(Q1+Q2) | -1.69% | -0.22% | -0.22% | -1.69% |
| B2 | Q5/Q1 | -2.21% | 0.25% | 0.25% | -2.21% |
| B2 | Q5/Q3 | -1.23% | 0.15% | 0.15% | -1.23% |
| B2 | Q3/Q1 | -1.00% | 0.10% | 0.10% | -1.00% |
| B2 | (Q4+Q5)/(Q1+Q2) | -1.70% | 0.22% | 0.22% | -1.70% |

Notes: Table shows the percentage difference of Vietnamese Q5/Q1, Q5/Q3, Q3/Q1 and (Q4+Q5)/(Q1+Q2) ratios from counterfactual baseline ratios at 2020 and 2100, and the maximum and minimum percentage difference from counterfactual baseline ratios observed during this time period. Q1 represents the income of the lowest expenditure quintile, and Q5 represents the income of highest expenditure quintile. Differences arose as a result of FUND's estimated climate change impacts on agricultural output, energy expenditure, expenditure building coastal defences and expenditure on reconstruction after storm damages. Results are aggregated direct and indirect effects from all four sectors. The case study was run from 2020 to 2100 for SRES scenarios A1B, A2, B1 and B2. The counterfactual baseline incomes assume no effects from climate change.

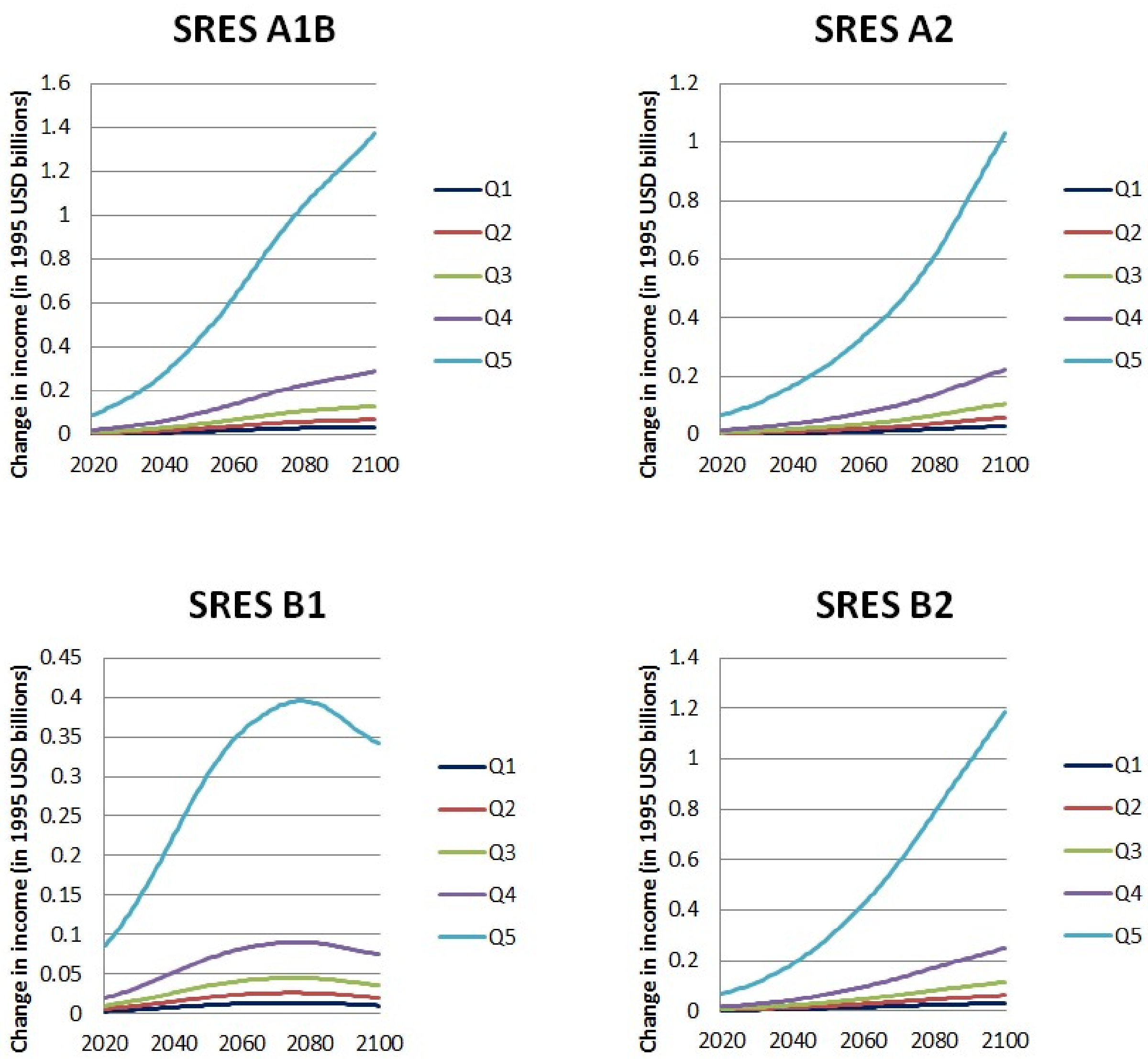
### 6.3.7 Zambia

As shown in Figure 6.13, cumulative impacts in absolute terms were unequally distributed across household groups, with higher expenditure quintiles experiencing greater deviations in incomes from the baseline. Impacts were positive for all household groups between 2020 and 2100, and continuously increased in all scenarios, except B1, where they rose to a peak around 2074 to 2077, and then fell.

When viewed as percentage changes from baseline incomes, these cumulative impacts did not alter any household group's income by more than 1.42%, at any time, in any scenario. As shown in Figure 6.14, the spread of percentage impacts across household groups at 2020 was 0.16 to 0.18 percentage points across all scenarios. These spreads increased in A1B and B2 to 0.42 and 0.61 percentage points respectively, decreased slightly then increased to 0.47 percentage points in A2, and increased slightly then decreased to 0.11 percentage points in B1. The ranking of proportional impacts across household groups remained the same across time and all scenarios, with higher expenditure quintiles seeing proportionately greater impacts.

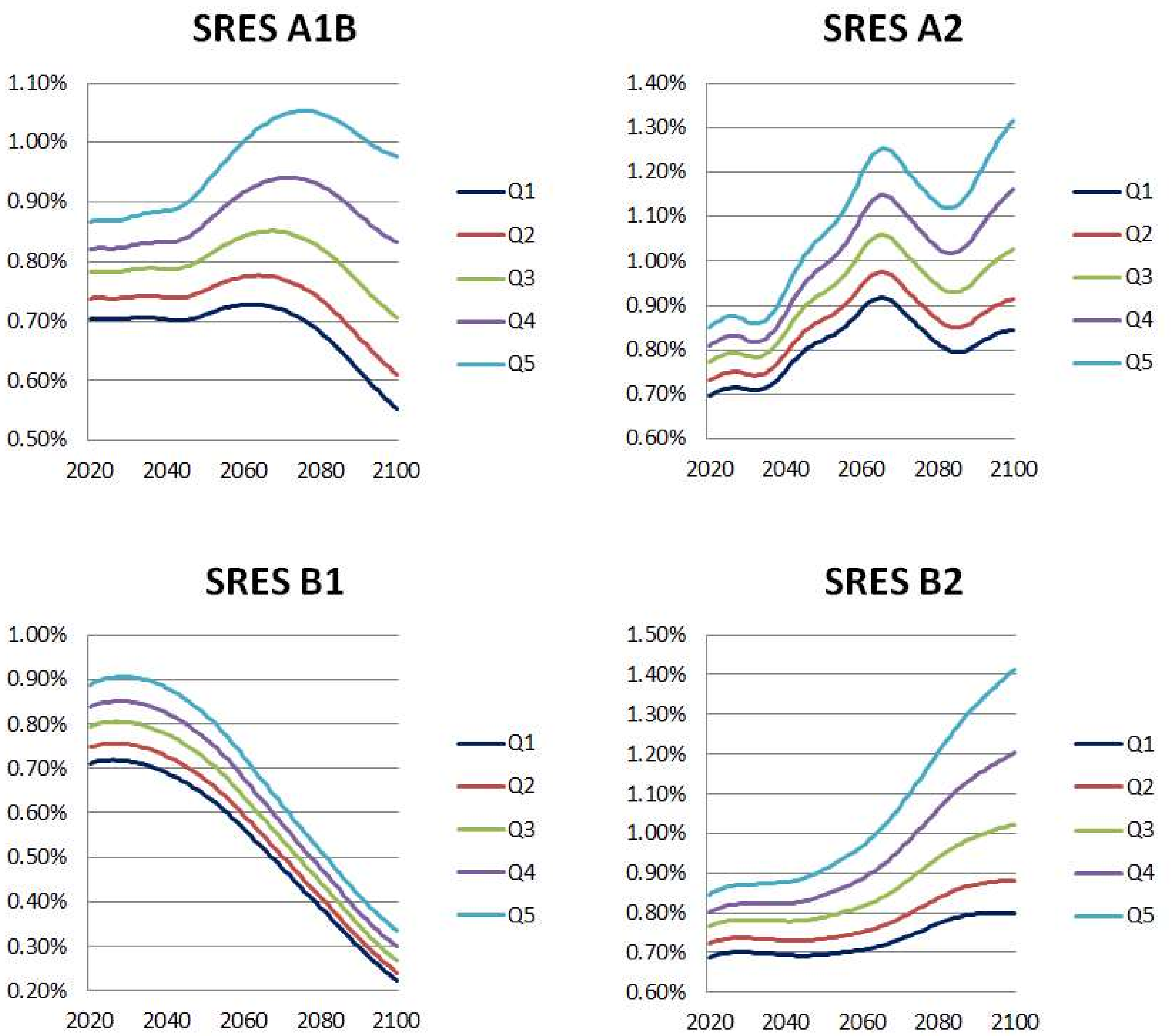
The baseline ratios, i.e. Q5/Q1, Q5/Q3, Q3/Q1 and (Q4+Q5)/(Q1+Q2) ratios in the Zambian SAM, were 22.08, 7.52, 2.93, and 9.71 respectively. Table 6.8 shows the percentage difference between these ratios after climate change impacts and the baseline ratios at 2020 and 2100, and the maximum and minimum percentage difference observed during this time period, in the four SRES scenarios. One can see that cumulative climate change impacts increased inequality throughout the time period, with ratios changing by between 0.04 and 0.61%.

Figure 6.13 – Cumulative changes (in 1995 USD billions) in Zambian household expenditure quintiles' incomes from counterfactual baseline incomes, in four SRES scenarios




Notes: Figure shows the cumulative changes in income for each Zambian household expenditure quintile as a result of FUND's estimated climate change impacts on agricultural output and energy expenditure. Results are aggregated direct and indirect effects from both sectors. The case study was run from 2020 to 2100 for SRES scenarios A1B, A2, B1 and B2. Q1 represents the income of the lowest expenditure quintile, and Q5 represents the income of highest expenditure quintile.

Figure 6.14 – Cumulative changes in Zambian household expenditure quintiles' incomes, as percentages of counterfactual baseline incomes, in four SRES scenarios




Notes: Figure shows the cumulative changes in incomes, expressed as percentages of counterfactual baseline incomes, for each Zambian household expenditure quintile, as a result of FUND's estimated climate change impacts on agricultural output and energy expenditure. Results are aggregated direct and indirect effects from both sectors. The case study was run from 2020 to 2100 for SRES scenarios A1B, A2, B1 and B2. The counterfactual baseline incomes assume no effects from climate change. Q1 represents the income of the lowest expenditure quintile, and Q5 represents the income of highest expenditure quintile.

Table 6.8 – Percentage difference of Zambian Q5/Q1, Q5/Q3, Q3/Q1 and (Q4+Q5)/(Q1+Q2) ratios from baseline ratios at 2020 and 2100, and maximum and minimum percentage difference observed during this time period, in four SRES scenarios

| Scenario | Ratio | Change at 2020 | Change at 2100 | Maximum change between 2020 and 2100 | Minimum change between 2020 and 2100 |
|---|---|---|---|---|---|
| A1B | Q5/Q1 | 0.16% | 0.42% | 0.42% | 0.16% |
| A1B | Q5/Q3 | 0.08% | 0.27% | 0.27% | 0.08% |
| A1B | Q3/Q1 | 0.08% | 0.15% | 0.15% | 0.08% |
| A1B | (Q4+Q5)/(Q1+Q2) | 0.13% | 0.36% | 0.36% | 0.13% |
| A2 | Q5/Q1 | 0.15% | 0.47% | 0.47% | 0.15% |
| A2 | Q5/Q3 | 0.08% | 0.29% | 0.29% | 0.07% |
| A2 | Q3/Q1 | 0.08% | 0.18% | 0.18% | 0.07% |
| A2 | (Q4+Q5)/(Q1+Q2) | 0.12% | 0.39% | 0.39% | 0.12% |
| B1 | Q5/Q1 | 0.18% | 0.11% | 0.19% | 0.11% |
| B1 | Q5/Q3 | 0.09% | 0.07% | 0.10% | 0.07% |
| B1 | Q3/Q1 | 0.08% | 0.04% | 0.09% | 0.04% |
| B1 | (Q4+Q5)/(Q1+Q2) | 0.14% | 0.09% | 0.15% | 0.09% |
| B2 | Q5/Q1 | 0.16% | 0.61% | 0.61% | 0.16% |
| B2 | Q5/Q3 | 0.08% | 0.39% | 0.39% | 0.08% |
| B2 | Q3/Q1 | 0.08% | 0.22% | 0.22% | 0.08% |
| B2 | (Q4+Q5)/(Q1+Q2) | 0.13% | 0.51% | 0.51% | 0.13% |

Notes: Table shows the percentage difference of Zambian Q5/Q1, Q5/Q3, Q3/Q1 and (Q4+Q5)/(Q1+Q2) ratios from counterfactual baseline ratios at 2020 and 2100, and the maximum and minimum percentage difference from counterfactual baseline ratios observed during this time period. Q1 represents the income of the lowest expenditure quintile, and Q5 represents the income of highest expenditure quintile. Differences arose as a result of FUND's estimated climate change impacts on agricultural output and energy expenditure. Results are aggregated direct and indirect effects from both sectors. The case study was run from 2020 to 2100 for SRES scenarios A1B, A2, B1 and B2. The counterfactual baseline incomes assume no effects from climate change.

## 6.4 Summary

This chapter presents the first case study, which uses FUND to explore the impact of climate change on income inequality in Egypt, Ethiopia, India, Mexico, the US, Vietnam and Zambia. It introduced the FUND model, explained how impacts estimated by the model would be used as inputs into the coupling methodology outlined in Chapter 5, described how FUND regional impact estimates were disaggregated into country-level impacts, and how budget constraints would be imposed to ensure that increases in expenditures don't automatically increase economic growth.

The chapter then introduced FUND's sectoral impact functions and the results they generated, which were used as inputs in this case study. Particular attention was drawn to the fact that FUND's agricultural impact functions, which have a large impact on FUND's overall results, are based on out-of-date studies that are more optimistic than more recent papers. In addition, implausibly large, i.e. greater than 100%, decreases in water output were observed for many countries and scenarios. This was most likely down to flaws in FUND's water impact function, which is unfortunately based on studies from 1995 and 1996 that were not published in journals and can no longer be found online, so the logic behind this function could not be examined. For scenario analysis to be useful, scenarios must be plausible and internally consistent. Greater than 100% decreases in output clearly do not meet this criterion. As such, water impacts were excluded from the case study. Chapter 8 does, however, use an IOA of the SAMs to estimate impacts from a unit change in water sector output, and then compares these to equivalent results generated for other sectors, to reflect on the possible effects that water sector impacts could have, relative to other sectors, on climate change income inequality effects. The strong influence of FUND's assumptions on results will also be discussed further in Chapter 9.

Finally, this chapter presented the results of the case study for all seven countries. Results were aggregated effects from all four sectors, agriculture, energy, SLR and storms. A breakdown of the sector-by-sector contributions to the aggregate results presented in this chapter can be found in Chapter 8.

Impacts, in absolute terms, were found to be positive for all household groups in all countries and scenarios. Absolute impacts were not, however, equally distributed across households, with higher expenditure or income households experiencing greater absolute impacts in all countries and scenarios. The same pattern across time was followed in all cases, with absolute impacts increasing, then peaking and falling, or continuously increasing for all household groups. The latter gave the impression of the peak having not yet been reached.

When expressed in percentage terms, which is what determines changes to inequality ratios, the distribution of relative impacts across household groups displayed a greater variety of patterns across countries and scenarios than were found with absolute impacts. Firstly, with regards to differences in relative impacts across different household groups, this spread was consistently narrow for some countries, and more sizable at times for others. In Egypt, India and Mexico, for example, spreads were small and ranged from 0.01 to 0.14, 0.05 to 0.25, and 0.02 to 0.16 percentage points respectively. The US was found to have the narrowest spread of relative impacts, ranging between only 0.03 and 0.08 percentage points. Somewhat greater variety was observed in Zambia, where differences in percentage impacts ranged from 0.11 to 0.61 percentage points, but only Ethiopia and Vietnam displayed more substantial differences at times between household groups, with differences in percentage impacts ranging from 0.1 to 1.2 and 0.03 to 2.42 percentage points respectively.

Even the maximum spread observed, 2.42 percentage points in Vietnam, was relatively small, particularly given that FUND's impact estimates are cumulative. One should keep in mind however, that FUND impact estimates do not alter any household's income by more than 2.64%, 2.72%, 1.3%, 0.78%, 0.17%, 4.24% and 1.42% in Egypt, Ethiopia, India, Mexico, the US, Vietnam and Zambia respectively.

The spread of percentage impacts across household groups often narrowed as time progressed; although it sometimes increased slightly first, before ending the time period more concentrated than at the start. This was the case for Egypt in B1, Ethiopia in all scenarios, India in A1B and B1, Mexico in all scenarios, the US in A1B, B1 and B2, Vietnam in A2 and B1, and Zambia in B1. In some cases, such as India in A2 and B2, and the US in A2, this appeared to be the direction of travel; however, the spread had not yet sufficiently narrowed from its peak, so the dispersion of percentage impacts in 2100 was equal to or greater than that in 2020. Similarly, in Vietnam in A1B and B2, the spread narrowed so much that it then inverted. This suggests that a similar pattern may have been seen in some other countries and scenarios had the model been run for a longer time period. Not all results, however, followed this overall pattern. The spread of percentage damages across Zambian household groups in A1B, A2 and B2, for example, generally increased with time, with the spread of relative impacts at 2100 being significantly larger than that at 2020. Meanwhile, the spread of Egyptian percentage impacts across households fluctuated in a relatively constrained range, despite the average percentage impact varying noticeably over time and, in A2 and B2, in patterns across time that were not observed in any other country.

With regards to which households experienced greater proportional impacts, this also varied across countries, and, on occasion, across time. In Ethiopia and India, lower expenditure or income quintiles always saw greater percentage impacts, while the opposite was true in Mexico and Zambia. A slightly less clear pattern was observed in the US, where, generally, higher income quintiles experienced greater impacts; although proportional impacts in all scenarios started off more skewed towards the third versus the fourth quintile, with this skew switching to the opposite as time progressed. Similarly, in Vietnam, lower expenditure quintiles saw greater impacts in A2 and B1, and at the start of A1B and B2; however, in the latter two scenarios, the opposite became true over time. Finally, the ranking of proportional impacts across household groups in Egypt displayed no clear pattern, with rankings changing across scenarios and time.

Changes in inequality ratios naturally reflected all these percentage impacts results. For example, countries where higher proportional impacts were experienced by lower expenditure quintiles saw inequality consistently reducing[120] across all ratios. Even Egypt and the US, where the spread of percentage impacts across household groups followed less clear patterns, changes in inequality ratios displayed distinct trends. In Egypt, inequality ratios decreased then increased in all scenarios, while in the US, inequality increased from the baseline at all times for all ratios and scenarios. Where lower or higher expenditure groups consistently experienced greater or lesser impacts, ratio changes were greatest for the Q5/Q1 ratio, followed by the Q5/Q3 and then the Q3/Q1 ratios. This was as one would expect mathematically. Whether the (Q4+Q5)/(Q1+Q2) ratio displayed greater changes than the Q5/Q3 ratio depended on the spacing of percentage impacts and initial incomes. The ranges of ratio changes displayed similar magnitudes to the ranges of differences in proportional impacts across household groups, with the ranges of ratio changes being -0.07% to 0.14%, -0.03% to -1.22%, -0.02% to -0.24%, 0% to 0.16%, 0.01% to 0.08%, -2.33% to 0.25%, and to 0.04% to 0.61% respectively for Egypt, Ethiopia, India, Mexico, the US, Vietnam and Zambia.

Chapter 8 analyses all the above results, along with those from the Alaska case study in Chapter 7, to address the research questions outlined in Chapter 2. This includes an exploration of the linkages in the SAM for each sector, along with a breakdown of the sector-by-sector contributions to the aggregate results presented in this chapter. This helps probe questions such as 'Which sectors have the greatest inequality effects?' and 'Are sector inequality effects consistent across countries?'. Results from this chapter are also examined across countries to analyse if starting levels or inequality and income appear to affect the extent that climate change impacts on inequality, and if inequality effects appear large enough to merit the trade-off of increased model complexity. Finally, Chapter 8 considers the sensitivity of results to uncertainty surrounding economic structures, and to different disaggregation of factor accounts, by comparing results using the 2016 US SAM to those using the US 2003 SAM, 2010 SAM and 2016 edu-SAM.

[120] Inequality was reduced as impacts were positive over the time period in all countries and scenarios.

# Chapter 7 – Impact of climate change on income inequality in Alaska

This chapter presents the second case study, which used a range of impact studies estimating the effects of climate change on different economic sectors in Alaska to explore the impact of climate change on Alaskan income inequality. An introduction to Alaska is provided in Section 7.1, along with a summary of the expected physical effects that climate change may have on the region. Section 7.2 describes the impact studies used in the case study. Section 7.3 explains the methodology, including how impact estimates were used as inputs in the input-output analysis (IOA) outlined in Chapter 5, and how scenarios were generated. Finally, the results of the case study are provided in Section 7.4. These results are analysed in Chapter 8, as this enabled results from the Climate Framework for Uncertainty, Negotiation and Distribution (FUND) case study in Chapter 6 to also be used to address the research questions outlined in Chapter 2.

## 7.1 Introduction to Alaska

Alaska is the largest United States (US) state by geographical area, covering 665,000 square miles, of which 86% is land and 14% is water (Census, 2012). With an estimated 737,000 residents in 2018 (Census, 2019a), however, it is also the most sparsely populated state, with approximately 0.77 people per square mile of land in 2018. 44% of Alaskans reside in the two largest cities, Anchorage and Fairbanks (DOLWD, 2019), and only 4% live in boroughs north of the Arctic Circle (DOLWD, 2019). It is a wealthy state, having the tenth highest personal income per capita in 2018 (BEA, 2019). In 2008, it was the most equal state, with an estimated income Gini coefficient of 0.403 (Census, 2019b). By 2017, income inequality had increased, with the Gini coefficient changing to 0.424. This made Alaska the second most equal state, coming just behind Utah. It is also a resource-rich state, with oil and gas, mining, and fishing. While Arctic oil and gas production is predominantly concentrated in Russia (Peters et al., 2011), between 1990 and 2004, Alaska was responsible for 18% of Arctic oil production and 3% of Arctic gas production (Peters et al., 2011). Other prominent economic sectors in Alaska include government, services, transportation and construction (Seung, 2014). The state pays citizens who have lived in the state for the full calendar year an annual dividend, which amounted to $1,600 per person in 2018, from the state-owned Alaska Permanent Fund. This sovereign wealth fund is funded through oil and investment revenue. Alaska also receives extensive federal government funding. In 2013, it received $3,604 in federal grants per capita (PEW, 2014). This was more than any other state. Alaska was also the third highest state recipient of total federal spending per capita in 2013, as when including grants, benefits, contracts and salaries and wages, it received $14,375 per person.

## 7.2 Alaskan impact studies

### 7.2.1 Introduction to Alaskan impact studies

As explored in Chapter 3, global warming in the Arctic has been approximately twice the global average (Cohen et al., 2014). In addition to Arctic climate processes potentially having a strong influence on the global climate system (Abbot et al., 2009; Holland et al., 2006; Lenton et al., 2008; Shakhova et al., 2010), the Arctic itself is expected to undergo large changes over the coming decades and centuries. These changes are likely to bring a mixture of opportunities and challenges to people living in the region (Alvarez et al., 2019). There is great uncertainty, however, surrounding the consequences of a warmer Arctic.

As a result of reduced sea-ice, for example, Arctic oceans may absorb more carbon dioxide ($CO_2$), and thus become more acidic (Thor et al., 2018), which could undermine calcifying species (Lischka and Riebesell, 2012), such as pteropods, mussels, and clams. In addition, changing ocean temperatures could lead to fish migrating from lower latitudes to higher latitudes, with invasive species possibly disrupting existing species (Frainer et al., 2017). On the other hand, warmer Arctic oceans and reduced sea ice might boost primary production through photosynthesising phytoplankton (Park et al., 2015), which, in turn, could increase Arctic fish stocks.

As another example, it is estimated that 25% of the world's undiscovered petroleum may be found in the Arctic (Lindholt and Glomsrød, 2012), with 28% of undiscovered oil and 14% of undiscovered gas thought to be found in Alaska and its waters. There may be fewer resources, however, than are estimated. Moreover, as sea-ice retreats and such reserves, including some onshore reserves, may become more accessible, costs are still anticipated to be high (Wood Mackenzie, 2006), due to difficult weather, including possibly more intense Arctic cyclones in summer (Day et al., 2018), the inherent challenges of offshore extraction, and the remoteness of sites, with their accompanying lack of existing infrastructure. As such, exploiting such assets may only be financially viable if prices are high (Petrick et al., 2017).

Different economic sectors in Alaska may, thus, see large and diverse impacts from climate change. As discussed, the Alaskan economy is particularly linked to the environment and natural resources, so these changes could, in turn, have large and diverse economic impacts on different households.

This case study does not claim to be a comprehensive and definitive study of the impact of climate change on income inequality in Alaska, but rather a first attempt to explore the subject.

Impact estimates could not be found for all the sectors that could be affected by climate change. No impact study could be found, for example, that estimated how reduced sea-ice might change Alaskan shipping output, due to 'unlocking' the Northwest Passage above Canada. Most research exploring the impact of reduced sea ice on shipping has focused on the Northeast Passage above Europe and Russia, as it is generally believed that the Northwest Passage is not likely to become financially viable (Lackenbauer and Lajeunesse, 2014; Stewart et al., 2007; Wilson et al., 2004).

An economic impact study also could not be found for Alaskan agriculture. Agriculture is currently a relatively small part of the Alaskan economy, but may grow in importance as Alaska warms. Lader et al. (2018) estimated, for a given climate scenario, that the Alaskan growing season length could increase from current levels by 48-87 days by the end of the century. It was not possible, however, to easily convert this into an estimated change in agricultural yield, as there isn't a straightforward relationship between growing season length and the latter (Kukal and Irmak, 2018).

In addition, while Melvin et al. (2017) provides some estimates of future coastal erosion in Alaska, without a land use analysis, which was beyond the scope of this thesis, it would be difficult to attribute these dryland losses across households or economic sectors.

This case study thus explored a subset of the sectors likely to be impacted by climate change, specifically, infrastructure, fisheries, oil extraction and tourism. Finally, one should reemphasise that there is extensive debate around whether fisheries and oil extraction will be boosted by climate change. The studies used in this case study explore scenarios where these sectors benefit, but one should remember that this is controversial. Chapter 8 does, however, use an IOA of the Alaskan social accounting matrix (SAM) to estimate impacts from a unit change to these sectors, and one could use this estimate the effects of less optimistic scenarios.

### 7.2.2 Infrastructure

One of the largest economic costs from climate change in Alaska may be damages to infrastructure due to increased freeze-thaw dynamics, cracking and subsidence from permafrost thaw, precipitation, and precipitation-caused flooding. Melvin et al. (2017) compiled an inventory of public Alaskan infrastructure, and then used the University of Alaska, Fairbanks' Scenarios Network for Alaska and Arctic Planning (SNAP) downscaled climate projections for Alaska in two scenarios, representative concentration pathway (RCP) 8.5 and RCP 4.5 (SNAP, 2017), along with reduced form permafrost equations and an infrastructure model tailored for northern latitudes, to estimate repair costs from damages to roads, railways, pipelines, airports and buildings between 2015 and 2099. The model incorporated replacement costs where infrastructure was estimated to be too badly damaged to be repaired, while costs unrelated to climate change, such as those associated with routine maintenance, were excluded. The quantity of infrastructure was also assumed to remain constant throughout the study. Finally, adaptation costs and benefits were also considered. Where the costs of adaptation were estimated to exceed the cost of repairing damages without adaptation, the latter was used for the cost estimate, i.e. it was assumed no adaptation took place.

Table 7.1 – Mean estimated infrastructure costs (in 2015 USD millions) in RCP 4.5 and RCP 8.5, with and without adaptation, broken down by infrastructure and damage type

| | | Mean estimated damages without adaptation (in 2015 USD millions) | | | | |
|---|---|---|---|---|---|---|
| | | **Flooding** | **Permafrost thaw** | **Precipitation** | **Freeze-thaw** | **Total** |
| **Roads** | **RCP 8.5** | 8600 | 700 | 2200 | -64 | 11000 |
| | **RCP 4.5** | 5900 | 190 | 1700 | -56 | 7700 |
| **Buildings** | **RCP 8.5** | Not modelled | 2800 | 350 | Not modelled | 3100 |
| | **RCP 4.5** | Not modelled | 2300 | 350 | Not modelled | 2600 |
| **Airports** | **RCP 8.5** | 690 | 360 | 440 | -15 | 1500 |
| | **RCP 4.5** | 470 | 250 | 320 | -13 | 1000 |
| **Railroads** | **RCP 8.5** | Not modelled | 620 | 0 | 0 | 620 |
| | **RCP 4.5** | Not modelled | 220 | 0 | 0 | 220 |
| **Pipelines** | **RCP 8.5** | Not modelled | 170 | Not modelled | Not modelled | 170 |
| | **RCP 4.5** | Not modelled | 16 | Not modelled | Not modelled | 16 |
| **Total** | **RCP 8.5** | 9300 | 4600 | 3000 | -78 | 17000 |
| | **RCP 4.5** | 6400 | 3000 | 2300 | -69 | 12000 |

| | | Mean estimated damages with adaptation (in 2015 USD millions) | | | | |
|---|---|---|---|---|---|---|
| | | Flooding | Permafrost thaw | Precipitation | Freeze-thaw | Total |
| Roads | RCP 8.5 | 390 | 700 | 1200 | -64 | 2200 |
| | RCP 4.5 | 370 | 190 | 910 | -56 | 1400 |
| Buildings | RCP 8.5 | Not modelled | 2800 | 10 | Not modelled | 2800 |
| | RCP 4.5 | Not modelled | 2300 | 5 | Not modelled | 2300 |
| Airports | RCP 8.5 | 85 | 360 | 290 | -15 | 720 |
| | RCP 4.5 | 82 | 250 | 210 | -13 | 540 |
| Railroads | RCP 8.5 | Not modelled | 620 | 0 | 0 | 620 |
| | RCP 4.5 | Not modelled | 220 | 0 | 0 | 220 |
| Pipelines | RCP 8.5 | Not modelled | 170 | Not modelled | Not modelled | 170 |
| | RCP 4.5 | Not modelled | 16 | Not modelled | Not modelled | 16 |
| Total | RCP 8.5 | 470 | 4600 | 1500 | -78 | 6500 |
| | RCP 4.5 | 450 | 3000 | 1100 | -69 | 4500 |

Notes: Table details costs of repairing or replacing Alaskan infrastructure damaged by climate change between 2015 and 2099 as estimated by (Melvin et al., 2017). Negative costs are benefits. All costs were changes relative to a baseline, where the latter assumed 'normal' weather and maintenance costs, but no impacts from climate change. Costs are estimated for roads, buildings, airports, railroads and pipelines for two climate scenarios, RCP 8.5 and RCP 4.5. Four different causes of damages were considered, flooding, permafrost thaw, precipitation and freeze-thaw dynamics, and models were run assuming and not assuming adaptation to climate change. Where adaptation costs exceeded costs of repairs, adaptation was assumed to not occur. The quantity of infrastructure was assumed to remain constant throughout the study.

Table 7.1 shows cumulative, undiscounted costs, in 2015 USD millions, for each scenario at the end of the time period, with and without adaptation, broken down by infrastructure and damage type. All impacts were changes relative to a baseline, where the latter assumed 'normal' weather and maintenance costs, but no impacts from climate change. For flooding and precipitation, there were estimated to be large benefits from adaptation, with total costs reducing by 95% and 50% respectively in RCP 8.5, and 93% and 52% respectively in RCP 4.5. Conversely, the estimated costs of adaptation to permafrost thaw exceeded the cost of repairs, while freeze-thaw cycles were estimated to decrease with climate change, and so reduce infrastructure maintenance costs. Without adaptation, flooding was responsible for the majority of damages, whereas with adaptation, permafrost thaw was the biggest problem. Similarly, without adaptation, roads were the source of approximately 65% of total costs, while with adaptation there were greater damages to buildings.

In this case study, cumulative costs were aggregated across infrastructure and damage types, so that four scenarios for increased expenditure on infrastructure were considered: RCP 4.5 with adaptation; RCP 4.5 without adaptation; RCP 8.5 with adaptation; and RCP 8.5 without adaptation. As can be seen in Table 7.1, total costs in these four scenarios amounted to 4.5, 12, 6.5 and 17 billion 2015 USD respectively.

### 7.2.3 Fisheries

As discussed earlier, fisheries are another sector likely to be impacted by climate change. Lam et al. (2016) used a Dynamic bioclimate envelope model (DBEM) to project changes in fisheries' yields in 10 Arctic countries and regions, including Alaska. Based on species' observed environmental preferences, along with a population model and an ecophysiology model, the DBEM projected how the quantity and location of oceanic species may evolve due to changes in oceanic temperature, salinity, acidity, sea-ice and other factors. Projections of these explanatory variables were obtained from four carbon-cycle-climate-models for Special Report on Emissions Scenarios (SRES) A2.

Lam et al. (2016) aggregated results for 62 harvested species, which historically have amounted to 93% of Arctic fisheries' collective output, and then compared the current catch potential in each country or region to its projected catch potential at 2050, assuming SRES A2. Results were quoted firstly when modelling climate change effects except ocean acidification, and then secondly when including ocean acidification as well. The Alaskan catch potential was estimated to increase above the 2000 catch level by 129% by 2050 with climate change but no ocean acidification, and by 126% with climate change and ocean acidification.

### 7.2.4 Oil extraction

Peters et al. (2011) uses the National Center for Atmospheric Research's Community Climate System Model to project future sea-ice coverage in the SRES A2 scenario. A partial equilibrium global energy model, called the Framework of International Strategic Behaviour in Energy and Environment (FRISBEE), is then used to project how this change in ice coverage may impact on future oil and gas supplies and the geographical sources of these supplies. The model took account of the current distribution of oil and gas production, likely positions of undiscovered reserves, operational costs, and access to infrastructure. As mentioned earlier, the financial viability of extracting Arctic reserves will be heavily dependent on prices, due to high expected costs of extraction. The oil price in the FRISBEE model was exogenous, due to the Organization of the Petroleum Exporting Countries

(OPEC), and set to $80 per barrel of oil equivalent in 2005 USD. In contrast, the gas price was determined by the model, as the gas market is not heavily influenced by a cartel. The projected increase in Alaskan oil supply was thus independent of increases in global demand from changes in gross domestic product (GDP) or population, as the FRISBEE model assumed that OPEC adjusted its supply to accommodate the latter and maintain fixed prices (Lindholt and Glomsrød, 2011). This meant that the estimated variation in Alaskan oil supply reflected the shifting financial viability of extracting Alaskan reserves as a result of climate change. In contrast, as gas prices were endogenous, the estimated alteration in Alaskan gas supply incorporated both changes in financial viability as a result of climate change and changes in gas demand due to GDP and population growth. As such, only the Peters et al. (2011) projected oil supply increase could be used in this case study, as the gas estimate could not be interpreted as a deviation from a 2050 baseline that incorporated the population and income aspects of SRES A2, but not effects from climate change. However, the estimated changes in oil supply still captured the majority of changes to total Alaskan oil and gas production as, in 2008 and 2050, Peters et al. (2011) estimated that oil was responsible for 75% and 79% of total Alaskan oil and gas production in million tonnes of oil equivalent (Mtoe).

While Peters et al. (2011) estimated that total Arctic oil production would increase by only approximately 11% between 2008 and 2050, Alaska was projected to see a much larger proportional increase of 282%.

### 7.2.5 Tourism

Tol and Walsh (2015) used data from the Hamburg Tourism Model (HTM) (Tol, 2010) to project changes, compared to 2009 levels, in tourists numbers to Alaska and other arctic regions in 2085, assuming SRES A2, B1 and B2. The HTM is an econometric model that simulates flows of tourists between 207 countries. The total number of global tourists provided by a given home country is a function of the population and income per capita in that home country. Whether those tourists choose to go abroad or to be domestic tourists, is a function of temperature and income per capita in the home country. Those that go abroad choose their destination based on the distance, temperature, attractiveness[121], and per capita income of destination countries. SRES A2, B1 and B2 population and income growth scenarios are explored, along with their accompanying temperature projections. A baseline was provided for each scenario that assumed changes in tourism levels due to evolving populations and incomes, but no changes from climate effects. This allowed 2085 results with and without climate change effects to be compared. As Alaska is not a country, it did not

[121] Attractiveness is measured using an index.

feature in the HTM; so Tol and Walsh (2015) assumed that tourist levels in Alaska grew at the same rate as that projected for Iceland[122].

Tol and Walsh (2015) estimated that tourism numbers in Iceland, and thus Alaska, would increase due to warmer weather. Non-domestic tourist numbers in 2085 in Iceland, taking climate change effects into account, were predicted in SRES A2, B1 and B2 to be 40%, 49%, and 50% respectively above projected 2085 tourist levels that didn't take climate change effects into account. This case study thus assumed that the projected number of tourists in Alaska in 2085, when taking climate change effects into account, would be these percentages above the 2085 baselines in each SRES scenario, where the baseline assumed changes in tourism due to evolving populations and incomes, but no changes from climate effects.

## 7.3 Methodology

### 7.3.1 Overview of methodology

This case study follows the same methodological approach as that used for the case study in Chapter 6. In short, the exogenous impacts taken from the aforementioned impact studies form a mixture of exogenous demand changes and exogenous output changes that can be modelled using equation (5.4), i.e.

$$\begin{pmatrix} \Delta\boldsymbol{x}^{(en)} \\ \Delta\boldsymbol{f}^{(en)} \end{pmatrix} = \boldsymbol{M}^{-1}\boldsymbol{N}\begin{pmatrix} \Delta\boldsymbol{f}^{(ex)} \\ \Delta\boldsymbol{x}^{(ex)} \end{pmatrix},$$

where $\boldsymbol{M} = \begin{bmatrix} (\boldsymbol{I} - \boldsymbol{A}_{11}) & \boldsymbol{0} \\ -\boldsymbol{A}_{21} & -\boldsymbol{I} \end{bmatrix}$ and $\boldsymbol{N} = \begin{bmatrix} \boldsymbol{I} & \boldsymbol{A}_{12} \\ \boldsymbol{0} & (\boldsymbol{A}_{22} - \boldsymbol{I}) \end{bmatrix}$. If the matrix of technical coefficients, $\boldsymbol{A}$, is arranged so that the $n$ row and column accounts with endogenous account totals are at the top and left respectively, with the remaining $m - n$ accounts with exogenous account totals at the bottom and right respectively, then $\boldsymbol{A}_{11}$, $\boldsymbol{A}_{12}$, $\boldsymbol{A}_{21}$ and $\boldsymbol{A}_{22}$ are matrices containing the technical coefficients in rows 1 to $n$, 1 to $n$, $n + 1$ to $m$, and $n + 1$ to $m$ respectively, and columns 1 to $n$, $n + 1$ to $m$, 1 to $n$, and $n + 1$ to $m$ respectively of $\boldsymbol{A}$. $\boldsymbol{I}$ and $\boldsymbol{0}$ are identity matrices of sizes $n$ and $m - n$ respectively. $\boldsymbol{x}^{(en)}$, $\boldsymbol{x}^{(ex)}$, $\boldsymbol{f}^{(ex)}$ and $\boldsymbol{f}^{(en)}$ are vectors of endogenous account totals, exogenous account totals, exogenous final demand and endogenous final demand respectively. As usual,

[122] As described in Chapter 1, there is a history of extrapolating estimates from one country to others in integrated assessments of climate change impacts.

government accounts[123], savings-investment and rest-of-the-world (ROW) accounts[124] were assumed to lie outside of the model and so comprised final demand. The reasoning behind this was detailed in Chapter 5.

As with the case study in Chapter 6, it was thus assumed that all parts of Alaska's economy grew by $\gamma_t = (1 + g_t)$ between $t - 1$ and $t$, where $g_t$ was exogenous GDP growth at time $t$, which differed across scenarios. For impacts associated with SRES scenarios, FUND's exogenous GDP growth rates for the USA were used. It was thus assumed that Alaska would grow at the same rate as the entire US. For infrastructure impacts, which were developed for two RCP scenarios, estimating growth rates was more complicated, as different Shared Socioeconomic Pathways (SSPs) could give rise to each RCP, so there is no unique matching between socioeconomic and greenhouse gas (GHG) concentration scenarios. This was explained in Chapter 3. RCPs 4.5 and 8.5 are, however, coherently paired with SSP2 and SSP5 respectively (Riahi et al., 2017), so these pairings were used in this case study. Projected USA GDP data for these scenarios, in 2005 USD billions, was downloaded from the SSP Public Database (Dellink et al., 2017; Riahi et al., 2017; SSP, 2018), and used to calculate growth rates for RCPs 4.5 and 8.5. Projections were available at five-year intervals, so linear interpolation was used, where necessary, to estimate growth within an interval.

As with Chapter 6, let $\boldsymbol{x}_t = \begin{pmatrix} {\boldsymbol{x}^{(en)}}_t \\ {\boldsymbol{x}^{(ex)}}_t \end{pmatrix}$ represent the vector of Alaskan account totals in a given scenario at time $t$, after climate impacts in time $t$ have been taken into account. Similarly, let $\Delta\boldsymbol{x}_t = \begin{pmatrix} \Delta{\boldsymbol{x}^{(en)}}_t \\ \Delta{\boldsymbol{x}^{(ex)}}_t \end{pmatrix}$ represent the vector of changes in Alaskan account totals at time $t$ due to climate impacts for the given scenario at time $t$. All impacts from the impact studies were cumulative impacts from a counterfactual economic baseline, $\widetilde{\boldsymbol{x}}_t$, where incomes were consistent with the given scenario, but there have hitherto been no economic impacts from climate change. This meant that

$$\boldsymbol{x}_t = \boldsymbol{x}_{SAM} \prod_{i=SAM+1}^{t} \gamma_i + \Delta\boldsymbol{x}_t,$$

where the year of the SAM, $t = SAM$, was 2008. Meanwhile, the counterfactual economic baseline, $\widetilde{\boldsymbol{x}}_t$, was calculated using

[123] The Alaska SAM contains both a federal government and an Alaskan state and local government account. Both of these accounts were assumed to lie outside of the model, and so formed part of final demand.
[124] There are three ROW accounts in the Alaskan SAM: a rest-of-the-United-States account, a ROW current account, and a ROW capital account.

$$\widetilde{\boldsymbol{x}}_t = \boldsymbol{x}_{SAM} \prod_{i=SAM}^{t} \gamma_i.$$

$\widetilde{\boldsymbol{x}}_t$, $\boldsymbol{x}_t$ and $\Delta\boldsymbol{x}_t$ all differed across scenarios. To fully facilitate comparisons between this case study and the FUND case study in the previous chapter, the Alaska SAM and exogenous impacts were converted into 1995 USD.

There are three household accounts in the Alaskan SAM, labelled low, medium and high-income households accounts. These are respectively defined to be households earning less than $25,000, $25,000 to $75,000, and more than $75,000 a year, in 2008 USD. Three inequality ratios[125] were thus used to assess changes in inequality: H/L, H/M and M/L, where L, M and H were the total incomes of low, medium and high-income households respectively[126]. The reasoning behind using inequality ratios to assess inequality, instead of an inequality index, such as the Gini coefficient, was detailed in Chapter 6.

These inequality ratios were determined from the applicable account totals in the $\boldsymbol{x}_t$ vector. The ratios were then compared to the equivalent baseline ratios to explore impacts on income inequality. Cumulative climate impacts at $t$ were also expressed as percentages of the baseline incomes at $t$; i.e., if ${x^{(u)}}_t$ represents the $u^{\text{th}}$ entry in $\boldsymbol{x}_t$, then

$$P^{(u)}{}_t = \frac{\Delta x^{(u)}{}_t}{\tilde{x}^{(u)}{}_t}.$$

These percentages captured the proportion of baseline income at time $t$ that was gained or lost due to cumulative climate change impacts at $t$, and so helped assess whether $\Delta x^{(u)}{}_t$ was large or small for each household group.

As the Alaskan impact studies, with the exception of the fisheries study, did not estimate the effect of impacts on macroeconomic variables, GDP impacts were also estimated in this case study. As $\boldsymbol{f}_t = \boldsymbol{f}_{SAM} \prod_{i=SAM+1}^{t} \gamma_i + \Delta\boldsymbol{f}_t$ in a given scenario at time $t$, where $\boldsymbol{f}_t$ represents the vector of final demands, i.e. payments from the accounts deemed to lie outside of the model, and

[125] While three inequality ratios were calculated, it should be noted that inequality is being captured using two rather than three dimensions, as (H/M)*(M/L) = H/L. Results for all three ratios were quoted to make changes to the upper part, lower part, and top and bottom of the income distribution explicitly clear.

[126] It's an assumption (and shortcoming) of input-output analysis that households do not transition between household groups. So there is an implicit assumption that the relative total number of people in each income group does not change over time. This means that ratios of total impacts and per capita impacts across the different household groups will be the same.

$\Delta \boldsymbol{f}_t = \begin{pmatrix} \Delta \boldsymbol{f}^{(en)}{}_t \\ \Delta \boldsymbol{f}^{(ex)}{}_t \end{pmatrix}$, then GDP was calculated as

$$GDP_t = \sum_{i=G_1}^{G_y} (\boldsymbol{x}_t - \boldsymbol{f}_t),$$

where $G_1$ to $G_y$ were the account numbers spanning the GDP accounts, i.e. labour, capital and indirect taxation accounts. Payments to GDP accounts from accounts outside of the model had to be subtracted from GDP account totals, as GDP excludes factor payments to and from ROW. Baseline GDP, $\widetilde{GDP}_t$, could similarly be calculated as , $\widetilde{GDP}_t = \sum_{i=G_1}^{G_y} (\widetilde{\boldsymbol{x}}_t - \widetilde{\boldsymbol{f}}_t)$, where $\widetilde{\boldsymbol{f}}_t$ was baseline payments from accounts outside of the model.

As the impact studies provided cumulative impact estimates at different points in time and, frequently, for different scenarios, results for different sectors were run separately, and not aggregated together. An alternative to this would have been to attempt to calibrate an impact function for each sector that would translate any temperature change into a sector impact, and so allow impacts to be generated across time for all scenarios. This is the approach taken in integrated assessment models (IAMs), such as FUND. One impact study for each sector, however, is clearly not sufficient to meaningfully propose a functional form for each sector and calibrate it. In addition, a first principles analysis of how, say, Arctic fisheries stocks may respond to different future climates is clearly beyond the scope of this thesis. Thus, no attempt was made to construct impact functions for this case study.

### 7.3.2 Translation of impact study estimates into exogenous inputs for IOA

Melvin et al. (2017) estimated costs of infrastructure adaptation and damage repairs were projected expenditure changes, and so formed exogenous demand changes, i.e. part of $\boldsymbol{f}^{ex}{}_{2099}$, in the subsequent IOA. As the estimates from Melvin et al. (2017) were for state infrastructure only, they were modelled as expenditure on the construction commodity funded by the Alaskan state and local (S&L) government account. As per chapter 6, a budget constraint was imposed by assuming that increased S&L government spending on construction was funded by reduced expenditure on all other commodities, with the reduction spread across commodities in proportion to S&L government's spending on those goods and services in the SAM.

Lam et al. (2016) estimated climate-change-induced cumulative increases in fisheries catch yields, in tonnes, at 2050 compared to 2000 levels. Estimates were provided both with and without considering the effects of ocean acidification. As the Alaska SAM was for 2008, the estimated percentage increases needed to be adjusted by the percentage change between the 2000 and 2008 Alaskan catches. Data from the Sea Around Us database (UBC, 2015), provided by the Institute for the Oceans and Fisheries at The University of British Columbia, indicated that the Alaskan fishing sector's catch, in tonnage, reduced by approximately 1.2% between 2000 and 2008. Thus, the FUND A2 USA exogenous growth rates were then used to inflate the SAM up to the baseline 2050 scenario, with the change in fisheries' output due to climate change then estimated to be the 2050 baseline fisheries output multiplied by $[([1+r]/[1-0.012])-1]$, where $r$ was the estimated percentage change from (V. W. Y. Lam et al., 2016). These estimated changes in fisheries' outputs due to climate change formed exogenous account total changes, i.e. part of ${\boldsymbol{x}^{ex}}_{2050}$, in the subsequent IOA.

The Alaskan SAM has one collective account for oil and gas production; however, only the projected oil supply increases in Peters et al. (2011) represents changes in production due to climate change. As discussed earlier, the estimated changes in gas supply also included changes in demand due to increased GDP and population, and thus could not be used in this case study. To isolate baseline 2050 oil production output, the oil and gas commodity account, and the rest of the SAM, was first inflated up to 2050 using SRES A2 FUND income growth rates. The value of 2050 total oil and gas commodity output then needed to be disaggregated into separate estimated baseline outputs for oil and gas. This was done in proportions indicated by the ratio of 2008 Alaskan annual production of barrels of oil, from McDowell (2017), times the 2008 average West Texas intermediate (WTI) crude oil price per barrel, to 2008 Alaskan annual production of thousands of cubic feet of gas, from McDowell (2017), times the 2008 average price per thousand cubic feet of gas. This indicated an 88% to 12% split of the 2050 total oil and gas commodity output between oil and gas respectively. Crude oil and gas prices were taken from the U.S. Energy Information Administration's database (EIA, 2019). The 282% increase indicated by Peters et al. (2011) was then applied just to the estimated 2050 baseline oil commodity output. This represented an exogenous account total change, and so formed part of ${\boldsymbol{x}^{(ex)}}_{2050}$, in the subsequent IOA.

McDowell (2010) estimated that out-of-state visitors spent USD 1.5 billion in Alaska between October 2008 and September 2009. The value of the USD decreased by only 0.36% between 2008 and 2009, and no data could be found around how 2008 Alaska tourist numbers differed from those in 2009. It was thus assumed that out-of-state tourists spent USD 1.5 billion in Alaska in 2008. To get the tourism 2085 baseline, which took account of evolving population and incomes, but not climate change effects, 1.5 billion 2008 USD was converted into 1995 USD millions, and then FUND income growth rates were used to project both the Alaska SAM and exogenous expenditure by tourists up to a 2085 baseline for the three SRES scenarios. From McDowell (2010), 40%, 49%, and 50% of baseline

2085 exogenous expenditure by tourists in A2, B1 and B2 respectively were then taken to be the change in exogenous expenditure by tourists due to increased tourism from climate change.

As can be seen in Appendix F, the Alaskan SAM does not have a tourism account. McDowell (2010), however, analysed 2006 to 2007 Alaskan tourist survey data, and concluded that 23%, 19%, 19%, 16%, 13% and 10% of visitor spending went on gifts/souvenirs, tours/activities, lodging, food/beverages, other spending, and transportation respectively. The tours/activities category excluded tour operators' fees, while the other spending category primarily consisted of buying holiday packages. In this case study, it was assumed that the change in exogenous expenditure by tourists due to increased tourism from climate change could be disaggregated across the Alaskan SAM to the 'other retail trade', 'entertainment', 'lodging', 'eating and drinking', 'admin and support services', and transportation commodity accounts respectively, in the proportions estimated by McDowell (2010). Spending on holiday packages was allocated to the admin and support services commodity account, as this account included services provided by travel agencies, tour operators and visitors' bureaus. Expenditure on transportation was further broken down across SAM transportation commodity accounts, i.e. 'air transportation', 'water transportation' and 'other transportation', in proportion to existing exogenous ROW and rest-of-the-US spending on these accounts. All these projected expenditure changes were exogenous demand changes, and so formed part of ${\boldsymbol{f}^{(ex)}}_{2085}$. Increased expenditure by out-of-state tourists was funded by people who don't live in Alaska, so no budget constraint was required, as this increase in spending represented an influx of new money into the Alaskan economy, not a redistribution of existing spending in the state.

## 7.4 Case study results

### 7.4.1 Infrastructure

The cumulative changes in infrastructure expenditure in 2099, sourced from Melvin et al. (2017), produced 37% or 99% increases in output of the construction commodity, compared to the counterfactual baseline with no impacts from climate change, in RCP 4.5 when respectively including and not including adaptation. In RCP 8.5, the increased infrastructure expenditure produced 19% and 49% increases in construction commodity output with and without adaptation respectively. The percentage changes for the two RCP 8.5 scenarios were lower than for their RCP 4.5 equivalents, due to the very high exogenous income growth rates in RCP 8.5.

The cumulative infrastructure expenditure in 2099 also produced 2.94% and 7.89% decreases in GDP from the counterfactual baseline in RCP 4.5, with and without adaption respectively, due to reduced state and local government spending on other goods and services. Similarly, in RCP 8.5, GDP was estimated to fall by 1.46% and 3.87% respectively with and without adaption.

As can be seen from Table 7.2, cumulative impacts in absolute terms were unequally distributed across household groups, with middle income households seeing the greatest impacts, and low income households the smallest impacts, in all scenarios with or without adaptation. If one looks at the relative impacts in Table 7.3, however, one can see that impacts, as percentages of baseline incomes, fell more heavily on lower income than higher income household groups, in all scenarios with or without adaptation. The range of percentage impacts across household groups was more than twice as wide in scenarios without adaptation as it was in scenarios with adaption. The range was 1.83 and 4.83 percentage points in RCP 4.5, respectively with and without adaptation, and 0.94 and 2.40 percentage points in RCP 8.5, respectively with and without adaptation.

As the impacts on all household groups were negative and, in percentage terms, fell more on low income households and less on high income households, increased infrastructure spending, in all scenarios, with and without adaption, produced increases in the three inequality ratios. As one can see from Table 7.4, ratios changed by 0.24% to 5.28%, depending on the scenario, level of adaptation and ratio. In all cases, the H/L ratio saw the greatest changes and the M/L ratio the least.

Table 7.2 – Infrastructure impacts: cumulative changes (in 1995 USD millions) at 2099 in Alaskan household income groups' incomes from counterfactual baseline incomes in two RCP scenarios, broken down into impacts with and without adaptation

| | **RCP 4.5 adaptation** | **RCP 4.5 no adaptation** | **RCP 8.5 adaptation** | **RCP 8.5 no adaptation** |
|---|---|---|---|---|
| **L** | -153 | -408 | -220 | -577 |
| **M** | -576 | -1542 | -826 | -2178 |
| **H** | -331 | -899 | -462 | -1258 |

Notes: Table shows estimated cumulative changes in Alaskan household income groups' incomes in 2099 due to direct and indirect economic costs of repairing Alaskan infrastructure damaged by climate change. H represents the total income of high income households (households earning more than $75,000 a year, in 2008 USD), M represents the total income of medium income households (households earning between $25,000 and $75,000 a year, in 2008 USD), and L represents the total income of low income households (households earning less than $25,000 a year, in 2008 USD). Changes are quoted in reference to a baseline in which there are no economic impacts from climate change. Results were estimated for two climate scenarios, RCP 4.5 and RCP 8.5, and are broken down into impacts assuming adaptation does or does not take place.

Table 7.3 – Infrastructure impacts: cumulative changes at 2099 in Alaskan household income groups' incomes, as percentages of counterfactual baseline incomes, in two RCP scenarios, broken down into impacts with and without adaptation

| | **RCP 4.5 adaptation** | **RCP 4.5 no adaptation** | **RCP 8.5 adaptation** | **RCP 8.5 no adaptation** |
|---|---|---|---|---|
| **L** | -3.20% | -8.54% | -1.60% | -4.20% |
| **M** | -2.73% | -7.31% | -1.36% | -3.59% |
| **H** | -1.36% | -3.70% | -0.66% | -1.80% |

Notes: Table shows estimated cumulative changes in Alaskan household income groups' incomes in 2099 due to direct and indirect economic costs of repairing Alaskan infrastructure damaged by climate change, with cumulative changes quoted as percentages of counterfactual baseline incomes. This baseline assumed there were no economic impacts from climate change. H represents the total income of high income households (households earning more than $75,000 a year, in 2008 USD), M represents the total income of medium income households (households earning between $25,000 and $75,000 a year, in 2008 USD), and L represents the total income of low income households (households earning less than $25,000 a year, in 2008 USD). Results were estimated for two climate scenarios, RCP 4.5 and RCP 8.5, and are broken down into impacts assuming adaptation does or does not take place.

Table 7.4 – Infrastructure impacts: percentage differences at 2099, due to cumulative impacts, of Alaskan H/L, H/M and M/L income ratios from baseline ratios, in two RCP scenarios, broken down into impacts with adaptation and impacts without adaptation

| | **Baseline** | **RCP 4.5 adaptation** | **RCP 4.5 no adaptation** | **RCP 8.5 adaptation** | **RCP 8.5 no adaptation** |
|---|---|---|---|---|---|
| **H/L** | 5.08 | 1.89% | 5.28% | 0.95% | 2.50% |
| **H/M** | 1.15 | 1.40% | 3.89% | 0.71% | 1.85% |
| **M/L** | 4.42 | 0.48% | 1.34% | 0.24% | 0.64% |

Notes: Table shows estimated cumulative percentage changes in H/L, H/M and M/L Alaskan income ratios in 2099 due to direct and indirect economic costs of repairing Alaskan infrastructure damaged by climate change. H represents the total income of high income households (households earning more than $75,000 a year, in 2008 USD), M represents the total income of medium income households (households earning between $25,000 and $75,000 a year, in 2008 USD), and L represents the total income of low income households (households earning less than $25,000 a year, in 2008 USD). Changes are quoted in reference to the 2008 baseline income ratios calculated from (Seung, 2014). Results were estimated for two climate scenarios, RCP 4.5 and RCP 8.5, and are broken down into impacts assuming adaptation does or does not take place. Positive percentages indicate increases in inequality

### 7.4.2 Fisheries

The Lam et al. (2016) projected 129% and 126% increases in fisheries commodity output, respectively including and not including the effects of ocean acidification, in SRES A2 at 2050, respectively produced 3.99% and 4.09% increases in GDP. The difference with and without acidification was small, as Alaskan fisheries harvest few species, such as clams, that are expected to be strongly affected by pH changes.

One can see from Table 7.5 that increases in fisheries yields benefited higher income households more than lower income households, both with and without the effects of ocean acidification. The range of percentage impacts across household groups was 3.58 and 3.67 percentage points, respectively with and without ocean acidification. While subsidence activities are not modelled, as the Alaska SAM only captures monetary flows, one should note that only around 0.3% of total Alaska fisheries tonnage is caught by subsistence fishers (UBC, 2015), so including subsistence activities is not likely to substantially change results.

Table 7.5 – Fisheries impacts: cumulative changes (in 1995 USD millions) in Alaskan household income groups' incomes from counterfactual baseline incomes, and cumulative changes in Alaskan household income groups' incomes, as percentages of counterfactual baseline incomes, at 2050 in SRES A2, broken down into impacts with and without the effects of ocean acidification

| | **With ocean acidification** | | **Without ocean acidification** | |
|---|---|---|---|---|
| | **Absolute change (in 1995 USD millions)** | **Percentage change from baseline** | **Absolute change (in 1995 USD millions)** | **Percentage change from baseline** |
| **L** | 27 | 0.96% | 28 | 0.98% |
| **M** | 253 | 2.03% | 259 | 2.07% |
| **H** | 652 | 4.54% | 667 | 4.65% |

Notes: Table shows estimated cumulative changes in Alaskan household income groups' incomes in 2050 due to direct and indirect economic impacts of climate change on Alaskan fisheries, and these estimated cumulative changes as percentages of counterfactual baseline incomes. This baseline assumed that there were no economic impacts from climate change. H represents the total income of high income households (households earning more than $75,000 a year, in 2008 USD), M represents the total income of medium income households (households earning between $25,000 and $75,000 a year, in 2008 USD), and L represents the total income of low income households (households earning less than $25,000 a year, in 2008 USD). Results were estimated for one scenario, SRES A2, and are broken down into impacts with and without ocean acidification.

The skew of relative impacts across household groups increased all three inequality ratios in both scenarios. One can see from Table 7.6, that the ratios increased by 1.05% to 3.63% depending on the ratio and scenario, with the H/L and M/L ratios consistently increasing respectively the most and least.

Table 7.6 - Fisheries impacts: percentage difference, due to cumulative impacts, of Alaskan H/L, H/M and M/L income ratios from baseline ratios, at 2050 in SRES A2, broken down into impacts with and without the effects of ocean acidification

| | **Baseline** | **With ocean acidification** | **Without ocean acidification** |
|---|---|---|---|
| **H/L** | 5.08 | 3.55% | 3.63% |
| **H/M** | 1.15 | 2.47% | 2.53% |
| **M/L** | 4.42 | 1.05% | 1.08% |

Notes: Table shows estimated cumulative changes in H/L, H/M and M/L Alaskan income ratios in 2050 due to direct and indirect economic impacts of climate change on Alaskan fisheries. Changes are quoted in reference to the 2008 baseline income ratios calculated from (Seung, 2014). H represents the total income of high income households (households earning more than $75,000 a year, in 2008 USD), M represents the total income of medium income households (households earning between $25,000 and $75,000 a year, in 2008 USD), and L represents the total income of low income households (households earning less than $25,000 a year, in 2008 USD). Results were estimated for one scenario, SRES A2, and are broken down into impacts with and without ocean acidification. Positive percentages indicate increases in inequality.

### 7.4.3 Oil extraction

The Peters et al. (2011) projected 282% cumulative increase in oil production in SRES A2 at 2050 was estimated to produce an 8.94% increase in Alaskan GDP. As shown in Table 7.7, in both absolute and percentage terms, this produced the largest benefits for high income households and the smallest benefits for low income households. These differences in percentage impacts were sizable, with the range of percentage impacts spanning 7.84 percentage points. As percentage impacts were more moderate for low income households, all inequality ratios, but particularly the H/L and M/L ratios, saw sizable increases. These changes are detailed in Table 7.8.

Table 7.7 – Oil impacts: cumulative changes (in 1995 USD millions) in Alaskan household income groups' incomes from counterfactual baseline incomes, and cumulative changes in Alaskan household income groups' incomes, as percentages of counterfactual baseline incomes, in SRES A2 at 2050

| | **Absolute change (in 1995 USD millions)** | **Percentage change from baseline** |
|---|---|---|
| **L** | 73 | 2.59% |
| **M** | 968 | 7.76% |
| **H** | 1495 | 10.42% |

Notes: Table shows estimated cumulative changes in Alaskan household income groups' incomes in 2050 due to direct and indirect economic impacts of climate change on Alaskan oil production, and these estimated cumulative changes as percentages of counterfactual baseline incomes. This baseline assumed that there were no economic impacts from climate change. H represents the total income of high income households (households earning more than $75,000 a year, in 2008 USD), M represents the total income of medium income households (households earning between $25,000 and $75,000 a year, in 2008 USD), and L represents the total income of low income households (households earning less than $25,000 a year, in 2008 USD). Results were estimated for one scenario, SRES A2.

Table 7.8 - Oil impacts: percentage differences, due to cumulative impacts, of Alaskan H/L, H/M and M/L income ratios from baseline ratios, in SRES A2 at 2050

| | **Baseline** | **Percentage change in ratio from baseline** |
|---|---|---|
| **H/L** | 5.08 | 7.64% |
| **H/M** | 1.15 | 2.47% |
| **M/L** | 4.42 | 5.04% |

Notes: Table shows estimated cumulative changes in H/L, H/M and M/L Alaskan income ratios in 2050 due to direct and indirect economic impacts of climate change on Alaskan oil production. Changes are quoted in reference to the 2008 baseline income ratios calculated from (Seung, 2014). H represents the total income of high income households (households earning more than $75,000 a year, in 2008 USD), M represents the total income of medium income households (households earning between $25,000 and $75,000 a year, in 2008 USD), and L represents the total income of low income households (households earning less than $25,000 a year, in 2008 USD). Results were estimated for one scenario, SRES A2. Positive percentages indicate increases in inequality.

### 7.4.4 Tourism

The 40%, 49% and 50% projected cumulative increases in tourism from Tol and Walsh (2015), at 2085 in SRES A2, B1 and B2 respectively, were estimated to increase Alaskan GDP by 1.41%, 1.72% and 1.75% respectively. One can see from Tables 7.9 and 7.10, that in both absolute and relative terms, middle income household groups experienced the largest increases in income, followed by high income and then low income household groups. This result held for all scenarios, with the range of percentage impacts between household groups being 0.73, 0.89, and 0.91 percentage points in SRES A2, B1 and B2 respectively. As can be seen from Table 7.11, the H/M ratio thus decreased and the H/L and M/L ratios increased in all scenarios.

Table 7.9 – Tourism impacts: cumulative changes (in 1995 USD millions) in Alaskan household income groups' incomes from counterfactual baseline incomes, in three SRES scenarios at 2085

| | **SRES A2** | **SRES B1** | **SRES B2** |
|---|---|---|---|
| **L** | 39 | 38 | 27 |
| **M** | 341 | 330 | 238 |
| **H** | 281 | 270 | 194 |

Notes: Table shows estimated cumulative changes in Alaskan household income groups' incomes in 2085 due to direct and indirect economic impacts of climate change on Alaskan tourism. Changes are in reference to a baseline, which assumed that there were no economic impacts from climate change. H represents the total income of high income households (households earning more than $75,000 a year, in 2008 USD), M represents the total income of medium income households (households earning between $25,000 and $75,000 a year, in 2008 USD), and L represents the total income of low income households (households earning less than $25,000 a year, in 2008 USD). Results were estimated for three scenarios, SRES A2, B1 and B2.

Table 7.10 – Tourism impacts: cumulative changes in Alaskan household income groups' incomes, as percentages of counterfactual baseline incomes, in three SRES scenarios at 2085

| | SRES A2 | SRES B1 | SRES B2 |
|---|---|---|---|
| L | 0.76% | 0.92% | 0.94% |
| M | 1.49% | 1.82% | 1.86% |
| H | 1.06% | 1.29% | 1.32% |

Notes: Table shows estimated cumulative changes in Alaskan household income groups' incomes in 2085, as percentages of counterfactual baseline incomes, due to direct and indirect economic impacts of climate change on Alaskan oil production. Changes are in reference to a baseline, which assumed that there were no economic impacts from climate change. H represents the total income of high income households (households earning more than $75,000 a year, in 2008 USD), M represents the total income of medium income households (households earning between $25,000 and $75,000 a year, in 2008 USD), and L represents the total income of low income households (households earning less than $25,000 a year, in 2008 USD). Results were estimated for three scenarios, SRES A2, B1 and B2.

Table 7.11 – Tourism impacts: percentage difference, due to cumulative impacts, of Alaskan H/L, H/M and M/L income ratios from baseline ratios, in three SRES scenarios at 2085

| | Baseline | SRES A2 | SRES B1 | SRES B2 |
|---|---|---|---|---|
| H/L | 5.08 | 0.31% | 0.37% | 0.37% |
| H/M | 1.15 | -0.42% | -0.52% | -0.53% |
| M/L | 4.42 | 0.73% | 0.89% | 0.90% |

Notes: Table shows estimated cumulative changes in H/L, H/M and M/L Alaskan income ratios in 2085 due to direct and indirect economic impacts of climate change on Alaskan tourism. Changes are quoted in reference to the 2008 baseline income ratios calculated from (Seung, 2014). H represents the total income of high income households (households earning more than $75,000 a year, in 2008 USD), M represents the total income of medium income households (households earning between $25,000 and $75,000 a year, in 2008 USD), and L represents the total income of low income households (households earning less than $25,000 a year, in 2008 USD). Results were estimated for three scenarios, SRES A2, B1 and B2. Positive (negative) percentages indicate increases (decreases) in inequality.

## 7.5 Summary

This chapter introduced a range of impact studies exploring the effects of climate change on different sectors in Alaska, and described how these results were translated into inputs for the IOA detailed in Chapter 5. Results were then presented for the different sectors; however, unlike the case study in Chapter 6, these results couldn't be aggregated, as the impact studies covered different scenarios and periods of time. Due to data limitations, this case study was only able to explore a subset of the sectors likely to be impacted by climate change, specifically, infrastructure, fisheries, oil extraction and tourism. In addition, there is extensive debate around whether fisheries and oil extraction will be boosted by climate change. The studies used in this case study explore scenarios where these sectors benefit, but one should remember that this is controversial. This case study, thus, did not claim to be a comprehensive and definitive study of the impact of climate change on income inequality in Alaska, but rather a first attempt to explore the subject.

For all sectors, impacts, in both absolute and percentage terms, were unequally distributed across household groups. While the costs of infrastructure repairs, in absolute terms, impacted on middle income households the most and lower income households the least, in percentage terms, the poorer the household the greater the experienced impact. As impacts were negative in all scenarios, inequality ratios consistently increased. With impacts on fisheries, higher income household groups were more affected, both in absolute and percentage terms, which, as impacts were positive both with and without the effects of ocean acidification, resulted in all inequality ratios increasing. The same was true for the effects of increased oil extraction. Finally, in both absolute and relative terms, the projected increases in tourism affected middle income households the most, followed by high and then low income households. This result held for all scenarios, and naturally produced a decrease in the H/M ratio, but increases in the H/L and M/L ratios.

Chapter 8 analyses the results from this case study, in combination with the results from the case study in Chapter 6, to address the research questions outlined in Chapter 2.

# Chapter 8 – Reflecting on climate change and income inequality in light of the case studies

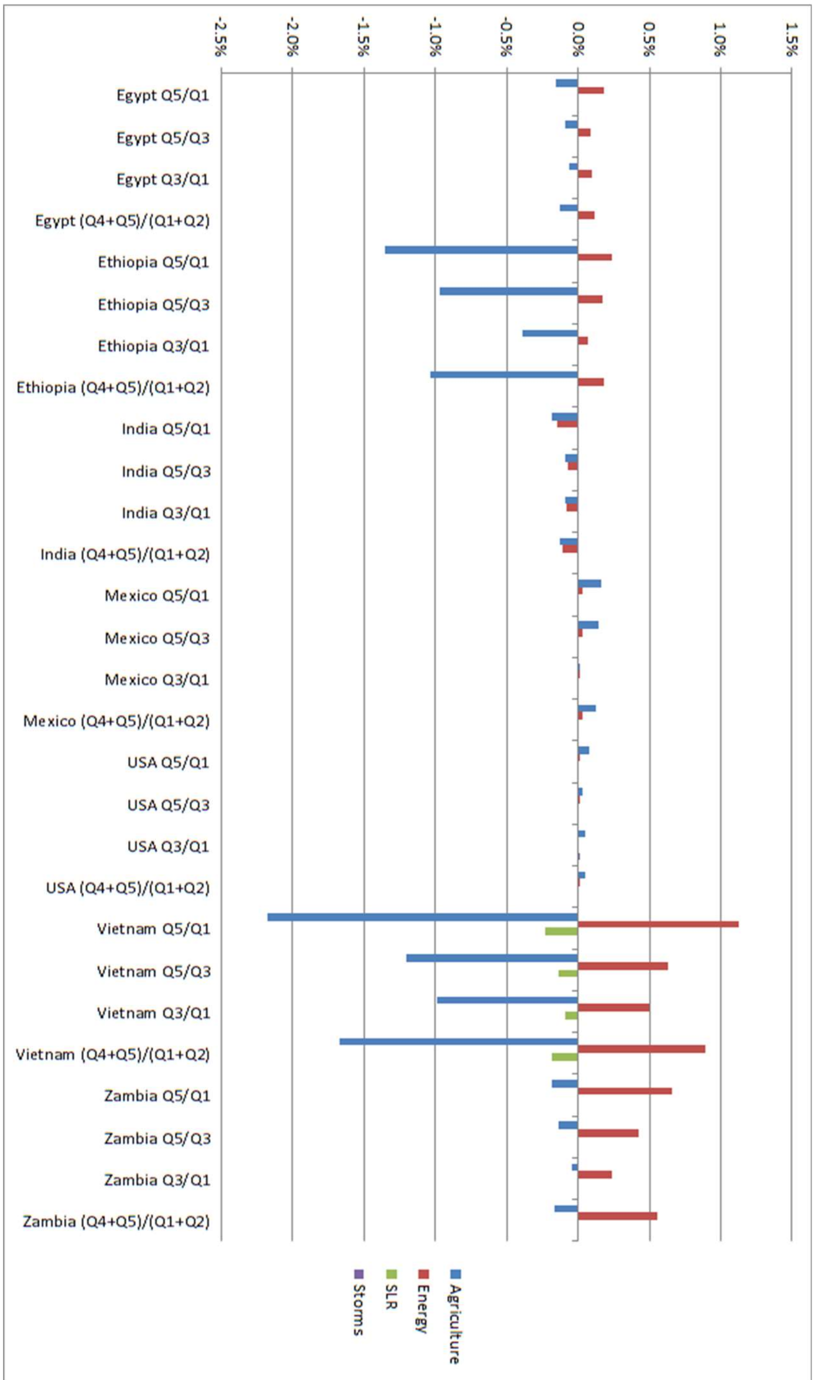
This chapter analyses the results from the case studies in Chapters 6 and 7 for insights on the research questions outlined in Chapter 2. Section 8.1 reflects on each research question in turn in light of the case study results. Meanwhile, by comparing results generated using the 2016 United States (US) SAM, which was used to derive the US estimates in the Chapter 6 case study, to those generated using the US 2003 SAM, 2010 SAM and 2016 edu-SAM, Section 8.2 explores the sensitivity of results to uncertainty surrounding economic structures and the extent of disaggregation of social accounting matrix (SAM) factor accounts.

## 8.1 Research questions in light of the case studies

### 8.1.1 Climate change induced changes to which sectors seem likely to have the greatest effect on within-country income inequality?

Figure 8.1 gives a breakdown, for each country and sector in the Climate Framework for Uncertainty, Negotiation and Distribution (FUND) case study, of the largest percentage change in each inequality ratio that was observed in any scenario at any point during the 2020 to 2100 time period. For nearly all countries and ratios, the largest percentage change in inequality ratios stemmed from the agricultural and energy sectors. The exceptions to this were Mexico and the United States (US), where, in comparison to the energy sector, construction costs from coastal defence against sea-level-rise (SLR) had slightly larger and similar magnitude maximum effects respectively on the Q3/Q1 ratio. In Egypt and India, the magnitudes of the largest percentage changes to each ratio from agriculture and energy were similar; although the net changes from these two sectors diminished and reinforced each other in Egypt and India respectively. In Ethiopia, Mexico, the US and Vietnam, the magnitudes from agricultural changes were notably greater than for those from changes in energy consumption. In contrast, the magnitudes of the largest ratio percentage changes from energy impacts were greater in Zambia than those from agricultural changes. In most cases, building coastal defences and repairing storm damages produced percentage changes in inequality ratios that were many multiples smaller than those arising from agricultural and energy impacts. Mexico and the US were exceptions, as differences between the magnitudes of maximum ratio percentage changes from energy and coastal defence impacts were less pronounced for these countries; although, as discussed, energy still generally produced larger changes to inequality. Ratio changes from repairing storm damages were small for all countries and ratios. In the US, however, they were approximately similar in magnitude to those from energy and coastal defence expenditure, which were also relatively small. Similarly, in Mexico, ratio changes from repairing storm damages were similar in magnitude to the relatively small SLR impacts.

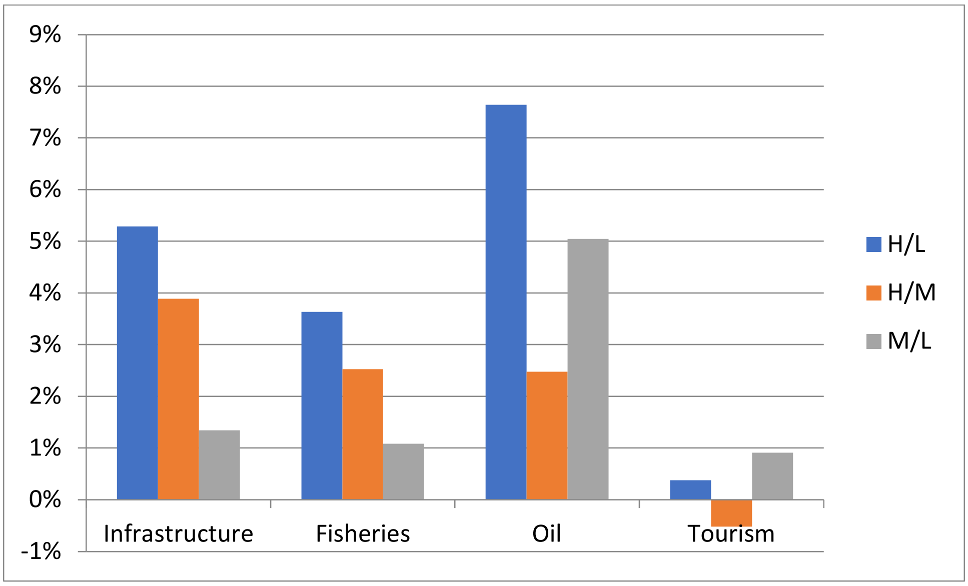
Figure 8.1 - Largest percentage change in each inequality ratio that was observed in any scenario at any point during the 2020 to 2100 time period, for each country and sector in the FUND case study




Notes: Figure shows, for each country in the FUND case study, the largest percentage changes in the four inequality ratios, Q5/Q1, Q5/Q3, Q3/Q1, (Q4+Q5)/(Q1+Q2), that were observed in any of the four scenarios, Special Report on Emissions Scenarios (SRES) A1B, A2, B1 and B2, at any point during the 2020 to 2100 time period. Q1 represents the income of the lowest expenditure or income quintile, while Q5 represents the income of highest expenditure or income quintile. Mexico and the US used income quintiles, while all other countries used expenditure quintiles. The percentage changes were driven by impacts to four economic sectors: agriculture, energy, coastal defence from sea-level rise (SLR), and repairs after tropical and extratropical storms. These impacts were estimated using the FUND model, as described in Chapter 6. Changes driven by impacts to each of the four FUND sectors are shown separately, where blue, red, green and purple bars respectively represent maximum changes driven by climate change impacts on agricultural output, energy demand, coastal defence expenditure, and repairing economic damages from tropical and extratropical storms. Positive (negative) changes indicate increases (decreases) in the relevant inequality ratio.

Figure 8.2 shows the largest percentage change in each Alaskan inequality ratio that was observed in any scenario at any time, for each sector in the Alaska case study. Changes in tourism produced the smallest result for each Alaskan inequality ratio and, with the exception of the change to the M/L ratio, these changes were of much smaller magnitudes than those arising from the other three sectors. Oil produced the largest percentage changes in the H/L and M/L ratios, while infrastructure had the greatest effect on the H/M ratio.

Figure 8.2 - Largest percentage change in each Alaskan inequality ratio that was observed in any scenario at any time, for each sector in the Alaska case study




Notes: Figure shows the largest percentage changes in the three Alaskan inequality ratios, H/L, H/M, and M/L, that were observed at any point in time in any of the scenarios in the Alaska case study, which is detailed in Chapter 7. H represents the total income of high income households (households earning more than $75,000 a year, in 2008 USD), M represents the total income of medium income households (households earning between $25,000 and $75,000 a year, in 2008 USD), and L represents the total income of low income households (households earning less than $25,000 a year, in 2008 USD). Maximum changes to the H/L, H/M and M/L ratios are represented using blue, red and green bars respectively. These percentage changes were driven by climate change impacts to four economic sectors: fisheries output, oil industry output, spending by tourists, and expenditure on infrastructure (road, buildings, airports, railroads, and pipelines) repairs after damage from flooding, permafrost thaw, precipitation and freeze-thaw dynamics. These impacts were estimated using impact studies, as described in Chapter 7. Changes driven by impacts to each of the four sectors are shown separately. Positive (negative) changes indicate increases (decreases) in the relevant inequality ratio.

There were two separate components driving the magnitudes of sector percentage changes to inequality ratios. The first was the magnitudes of the exogenous changes to sectors, as estimated by FUND and the Alaskan impact studies, which were then used as inputs in the input-output analysis (IOA). The second was the economic structure of each country, specifically the extent that a unit change to each sector would impact on the different household groups. Let us now explore both of these drivers in turn.

As was seen in Chapter 7, the Alaskan impact studies estimated extremely large percentage changes, approximately 130% and 280% respectively, to the fisheries and oil sectors. Relatively smaller changes were estimated to the construction sector from infrastructure repairs and sectors associated with tourism, with these changes averaging at approximately 19 to 99% and 40 to 50%, depending on the scenario. Given the baseline sizes of these sectors in the Alaskan economy, these percentage changes amounted to large exogenous changes from oil and infrastructure. These were, respectively, approximately 6 to 7 and 4 to 5 times larger than those from tourism. Exogenous impacts from fisheries were approximately double those from tourism. It is, thus, not surprising that oil and tourism respectively produced particularly large and small changes in inequality ratios in the case study in Chapter 7, nor that infrastructure produced relatively large changes. That fisheries produced sizable impacts, however, suggests that a unit change in fisheries must have a particularly large impact on the inequality ratios.

Meanwhile, as shown in Figure 6.1 in Chapter 6, FUND typically estimated much larger relative impacts for agriculture, water and energy than for other sectors. In the US in Special Report on Emissions Scenarios (SRES) A1B, for example, agricultural output and energy demand were estimated to change by 8.2% and 8.8% respectively, while construction expenditures from repairing storm damages and coastal protection were estimated to change by only 0.3% and less than 0.1% respectively. When taking into account the relative baseline sizes of the sectors, agriculture and energy still produced the largest exogenous changes. This can be seen in Appendix G, which shows FUND estimated exogenous changes across time for each sector, scenario and country. In this light, it is not surprising that agriculture and energy were typically found to produce the largest effects on inequality ratios. For Mexico and the US, however, the effects of a unit change on the Q3/Q1 ratio must be significantly larger for SLR than for energy, as SLR produced larger and similar effects respectively in the case study in Chapter 6, despite FUND estimated exogenous effects on energy to be approximately 40 and 90 times greater than those from SLR.

Moving on to the second driver, to explore the extent that a unit change to each sector would impact on the different household groups, increases of USD 1 billion, in 1995 USD billions[127], in agricultural output, water output, energy expenditure, coastal defence expenditure and storm damage repairs expenditure were inputted into the model used in Chapter 6 and 7, i.e.

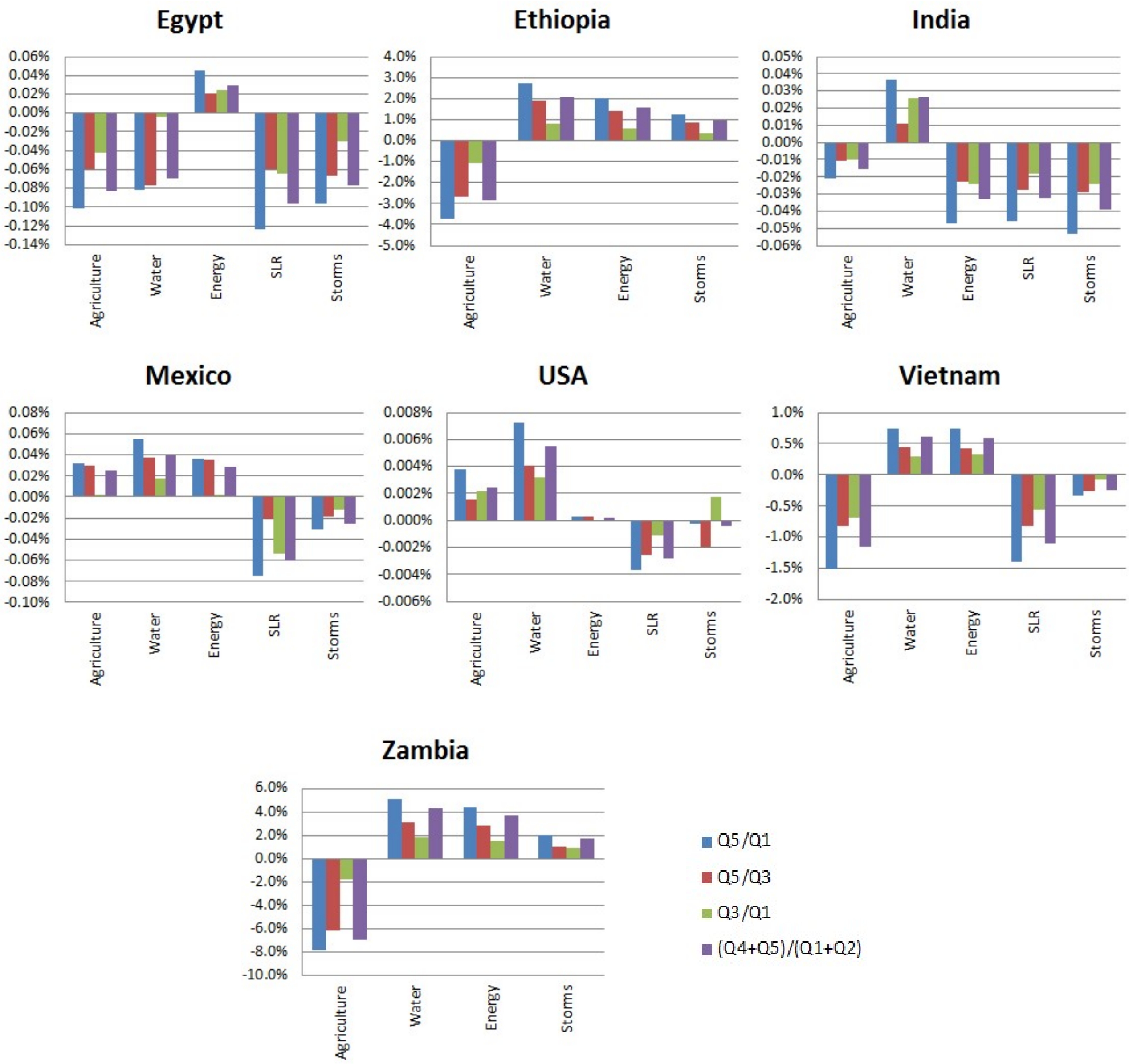
$$\begin{pmatrix}\Delta\boldsymbol{x}^{(en)}\\ \Delta\boldsymbol{f}^{(en)}\end{pmatrix} = \boldsymbol{M}^{-1}\boldsymbol{N}\begin{pmatrix}\Delta\boldsymbol{f}^{(ex)}\\ \Delta\boldsymbol{x}^{(ex)}\end{pmatrix}.$$

For energy, coastal defence and storms, the same budget constraints were imposed as for the FUND case study. Water was included, even though the water impacts from FUND could not be used in

[127] 1995 USD billions were used as the SAMs used in the case studies in Chapters 6 and 7 were all in 1995 USD billions.

Chapter 6, to probe to what extent this sector, which is likely to be affected by climate change, may, relative to other sectors, impact on income inequality ratios.

Figure 8.3 – For each SAM in the FUND case study, effects on inequality ratios of increases of USD 1 billion (in 1995 USD billions) in, each in turn, agricultural output, water output, energy expenditure, coastal defence expenditure and storm damage repairs expenditure




Notes: Figure shows, for each of the seven countries in the FUND case study, the effects on inequality ratios of increases of USD 1 billion (in 1995 USD billions) in, taking each in turn, agricultural output, water output, energy expenditure, expenditure on coastal defence, and expenditure on repairing storm damages. Results are shown separately for each sector. Effects were calculated using the model described in Section 8.1.1 of this chapter. Q1 represents the income of the lowest expenditure or income quintile, while Q5 represents the income of highest expenditure or income quintile. Mexico and the US used income quintiles, while all other countries used expenditure quintiles. Positive (negative) changes indicate increases (decreases) in the relevant inequality ratio.

The results of this analysis are displayed in Figure 8.3. A unit increase in expenditure on coastal defence was the only sector that had a consistent effect on inequality ratios across all countries, which was to decrease inequality. Unit increases in all other sectors produced effects that varied by country. Increased energy expenditure, for example, increased inequality ratios in all countries, except India. Similarly, increased water output increased inequality ratios in all countries, except Egypt. Generally, sectors changed all inequality ratios in a country in the same direction. Repairing storm damages in the US was the one exception to this, where Q3/Q1 increased, while all other inequality ratios decreased.

One can see that while agriculture and energy results typically dominated impacts in the FUND case study, when one is dealing with unit increases, these sectors did not always produce the largest magnitude impacts. In India, for example, agriculture produced smaller inequality effects for all ratios than every other sector. In Mexico and the US, as predicted earlier in the analysis, unit changes in construction from SLR produced much larger impacts on the Q3/Q1 ratio than unit changes in energy. Conversely, impacts from repairing storm damages and building coastal defences generally produced relatively small results in the FUND case study. In this unit change analysis, however, these sectors were responsible for some of the largest inequality changes in Egypt and India, while, in Mexico and Vietnam, the unit increase in coastal defence spending produced some of the largest impacts. This demonstrates that, if the FUND model is incorrect about the small relative magnitude of impacts from SLR and storms, spending on coastal defence and storm damage repairs has the potential to cause greater inequality effects than the FUND case study indicates. Similarly, effects on inequality ratios from unit changes in water output were relatively large in all countries, which demonstrates that this sector also has the potential to produce sizable inequality effects.

Appendix H shows how the impacts in Figure 8.3 are decomposed into direct and indirect effects. Direct impacts are the change in inequality ratios resulting from delivering only the additional exogenous unit of, say, agriculture. These were determined from the technical coefficient matrix, $\boldsymbol{A}$, by taking the technical coefficient for the exogenous commodity to its activity account, and multiplying it by the technical coefficient for its activity to a value-added account, and then the technical coefficient for that value-added account to a household group. This process was repeated for all value-added accounts and all household groups to determine the total direct impact of a unit change in the given commodity on each household group, from which the direct impacts on inequality ratios could be calculated. Indirect impacts were then all remaining changes in inequality ratios. Indirect impacts were brought about, for example, as increased quantities of other products required in the exogenous commodity's production recipe also required additional production of goods used in their own production processes, and so on, or, as changes in households' incomes resulted in changes in the quantities of consumer goods bought, which, in turn, changed production requirements further, etc. Whether direct or indirect effects had a stronger impact on inequality ratios depended on how interconnected the sector seeing the exogenous change was with the rest of the economy and household groups, and the extent to which it directed income unevenly across household groups compared to the skew of income across household groups generated by stimulated other sectors of the economy.

The breakdown of impacts into direct and indirect effects illustrates the importance of taking a macroeconomic approach and considering how sectors impact on one another, rather than modelling each sector individually and then summing the results, as was done in Rozenberg and Hallegatte (2015). As one can see in Appendix H, while some impacts were nearly entirely composed of direct effects, for others, indirect effects were far greater. For example, when looking at impacts in India from expenditure on repairing storm damages, 90% of the impacts on the Q5/Q1 inequality ratio were direct effects. In contrast, when looking at impacts in the US from a change in water utilities output, only 11% of the impacts on the Q3/Q1 inequality ratio were direct. In some cases, direct and indirect effects were even found to move inequality ratios in opposite directions. In Egypt, for example, the direct impact of a unit increase in agricultural production was to decrease the Q5/Q1 ratio by 0.2%, whereas the indirect impacts increased the Q5/Q1 ratio by 0.1%, leaving an overall decrease of 0.1%. Thus, in many cases, taking a microeconomic approach and then summing the results would produce a very incomplete picture.

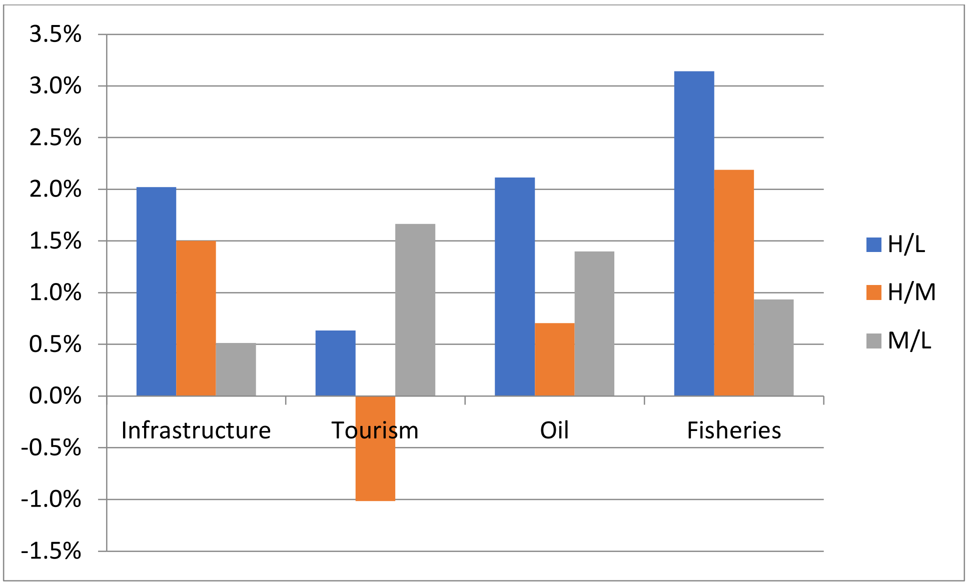
The same approach was taken for Alaska, only modelling, each in turn, increases of USD 1 billion, in 1995 USD billions, in fisheries output, oil output, expenditure on tourism and expenditure on infrastructure repairs. For the latter, the same budget constraint was imposed as for the Alaskan case study, and no budget constraint was imposed for tourism expenditure, once again, as per Chapter 7.

Results are shown in Figure 8.4. One can see that unit changes to fisheries had the largest impact on H/L and H/M ratios, while tourism had the largest impact on the M/L ratio. The fact that oil had the largest impact on the H/L and M/L ratios in the Alaska case study was thus down to the size of the exogenous increase in oil output relative to that for fisheries output and tourism expenditure.

A decomposition of these impacts into direct and indirect effects can be found in Appendix H. Once again, indirect effects were sometimes minor and sometimes very influential. For example, when looking at tourism, only 1% of impacts on the H/M ratio were indirect, whereas, when looking at fisheries output, 84% of the impacts on the M/L ratio were indirect. As before, sometimes direct and indirect effects reinforced each other, while, at other times, they acted in opposite directions.

Impacts on all ratios from a change to oil output were examples of the former, whereas impacts on all ratios from a change in expenditure on infrastructure were examples of the latter.

Figure 8.4 – Effects on Alaskan inequality ratios of increases of USD 1 billion (in 1995 USD billions) in, each in turn, expenditure on infrastructure, increased tourism, oil output, and fisheries output




Notes: Figure shows the effects on Alaskan inequality ratios of increases of USD 1 billion (in 1995 USD billions) in, taking each in turn, expenditure on infrastructure, increased tourism, oil output, and fisheries output. Results are shown separately for each sector. Effects were calculated using the model described in Section 8.1.1 of this chapter. Q1 represents the income of the lowest expenditure or income quintile, while Q5 represents the income of highest expenditure or income quintile. Mexico and the US used income quintiles, while all other countries used expenditure quintiles. Positive (negative) changes indicate increases (decreases) in the relevant inequality ratio.

In short, while the FUND case study indicated that agriculture and energy expenditure, particularly agriculture, are likely to be the sectors responsible for the largest inequality effects, an analysis of unit changes to each sector suggested that water, SLR and storms impacts have the potential to also generate large effects, if the FUND model is incorrect in estimating that impacts from these sectors will be far smaller than those for other sectors. Moreover, even when examining just the FUND case study, the dominance of the agricultural sector results had exceptions, as the energy sector produced the largest magnitude results in Zambia. Finally, in some countries, the inequality effects from agriculture and energy expenditure reinforced each other, while in others, they moved inequality in opposite directions. They thus have the potential to cancel each other out, in which case, smaller impacts from other sectors could instead determine the change in inequality.

Meanwhile, the Alaskan case study found that changes to infrastructure, fisheries and especially oil are most likely to be responsible for changes to inequality. Modelling unit changes to the different sectors, however, implied that fisheries and tourism could play larger roles than the Alaska case study suggested. The magnitudes of impacts from tourism in this analysis were closer to those from other sectors than was observed in the case study, and fisheries were even found to have the largest impact on two ratios.

### 8.1.2 Do impacts to certain sectors consistently increase within-country income inequality across different economies? Or do impacts in some countries reduce inequality and in other countries increase inequality?

As smaller impacts can be difficult to see on graphs, Table 8.1 details the data behind Figure 8.1. One can see that only effects due to increased spending on coastal defence impacted on inequality in all countries in the same way; in this case, by consistently decreasing inequality. Table 8.1 would suggest that this is very nearly also true for increased spending on repairing storm damages, as this sector appeared to decrease inequality in all cases, except for the American Q3/Q1 ratio. If one looks at the sector-by-sector unit change analysis in Figure 8.3, however, it becomes clear that this is only true if the extremely small estimated impacts from storm damages in Ethiopia and Zambia are ignored, as a unit change to this sector in these countries also increased inequality.

In addition, as was discussed in Chapter 6 and one can also see from Appendix G, in Mexico and the US, there were small projected reductions in energy expenditure for the first few decades of analysis, due to savings from reduced space heating, which were later overwhelmed by increased costs of space cooling. This meant that for these countries, effects from energy expenditure acted on inequality in opposite ways at different points in time. Although, for both countries, the magnitudes of benefits from reduced space heating were much smaller, and shorter-lived, than the subsequent costs from increased space cooling.

Similarly, while FUND estimated positive agricultural impacts throughout the time period used for the FUND case study, had the model been run for longer, the benefits of carbon dioxide ($CO_2$) fertilisation would have been cancelled out by growing negative impacts from climate change level effects. This would have been true for all countries. Thus, agriculture is another sector that could produce different inequality effects within a country at different points in time.

Table 8.1 - Largest percentage change in each inequality ratio that was observed in any scenario at any point during the 2020 to 2100 time period, for each country and sector in the FUND case study

| | Ratio | Baseline | Agriculture | Energy | SLR | Storms |
|---|---|---|---|---|---|---|
| Egypt | Q5/Q1 | 4.783 | -0.160% | 0.182% | -0.005% | Negligible |
| | Q5/Q3 | 2.704 | -0.094% | 0.084% | -0.002% | Negligible |
| | Q3/Q1 | 1.769 | -0.067% | 0.098% | -0.003% | Negligible |
| | (Q4+Q5)/(Q1+Q2) | 2.908 | -0.132% | 0.117% | -0.004% | Negligible |
| Ethiopia | Q5/Q1 | 6.042 | -1.357% | 0.240% | None | Negligible |
| | Q5/Q3 | 2.952 | -0.969% | 0.170% | None | Negligible |
| | Q3/Q1 | 2.047 | -0.392% | 0.070% | None | Negligible |
| | (Q4+Q5)/(Q1+Q2) | 3.338 | -1.034% | 0.184% | None | Negligible |
| India | Q5/Q1 | 6.114 | -0.180% | -0.151% | -0.010% | -0.006% |
| | Q5/Q3 | 3.016 | -0.092% | -0.073% | -0.006% | -0.003% |
| | Q3/Q1 | 2.028 | -0.088% | -0.078% | -0.004% | -0.003% |
| | (Q4+Q5)/(Q1+Q2) | 3.632 | -0.131% | -0.106% | -0.007% | -0.004% |
| Mexico | Q5/Q1 | 8.046 | 0.158% | 0.034% | -0.006% | -0.003% |
| | Q5/Q3 | 4.347 | 0.146% | 0.032% | -0.002% | -0.002% |
| | Q3/Q1 | 1.851 | 0.011% | 0.002% | -0.004% | -0.001% |
| | (Q4+Q5)/(Q1+Q2) | 4.303 | 0.126% | 0.026% | -0.005% | -0.003% |
| USA | Q5/Q1 | 14.673 | 0.080% | 0.009% | -0.002% | -0.001% |
| | Q5/Q3 | 3.512 | 0.034% | 0.010% | -0.002% | -0.007% |
| | Q3/Q1 | 4.178 | 0.046% | -0.001% | -0.001% | 0.006% |
| | (Q4+Q5)/(Q1+Q2) | 6.074 | 0.050% | 0.006% | -0.002% | -0.002% |
| Vietnam | Q5/Q1 | 6.501 | -2.181% | 1.129% | -0.231% | -0.004% |
| | Q5/Q3 | 2.786 | -1.199% | 0.631% | -0.137% | -0.003% |
| | Q3/Q1 | 2.333 | -0.993% | 0.495% | -0.094% | -0.001% |
| | (Q4+Q5)/(Q1+Q2) | 3.662 | -1.672% | 0.894% | -0.182% | -0.003% |
| Zambia | Q5/Q1 | 22.075 | -0.182% | 0.660% | None | Negligible |
| | Q5/Q3 | 7.525 | -0.140% | 0.425% | None | Negligible |
| | Q3/Q1 | 2.934 | -0.041% | 0.233% | None | Negligible |
| | (Q4+Q5)/(Q1+Q2) | 9.706 | -0.161% | 0.559% | None | Negligible |

Notes: Table shows, for each country in the FUND case study, the largest percentage changes in the four inequality ratios, Q5/Q1, Q5/Q3, Q3/Q1, (Q4+Q5)/(Q1+Q2), that were observed in any of the four scenarios, SRES A1B, A2, B1 and B2, at any point during the 2020 to 2100 time period. Q1 represents the income of the lowest expenditure or income quintile, while Q5 represents the income of highest expenditure or income quintile. Mexico and the US used income quintiles, while all other countries used expenditure quintiles. The percentage changes were driven by climate change impacts on four economic sectors, agricultural output, energy demand, coastal defence expenditure from sea-level rise (SLR), and expenditure on repairing economic damages from tropical and extratropical storms. These impacts were estimated using the FUND model, as described in Chapter 6. Changes driven by impacts to each of the four FUND sectors are shown separately, and are compared to the baseline inequality ratios, i.e. initial inequality ratios calculated from the relevant countries' social accounting matrices (SAMs). Positive (negative) changes indicate increases (decreases) in the relevant inequality ratio. Changes from impacts on coastal defence expenditure were not modelled for Ethiopia or Zambia, as these countries are landlocked.

None of the sectors in the Alaska and FUND case studies overlapped, so the Alaska case study could not be included in this analysis.

### 8.1.3 Do certain household groups seem particularly vulnerable across economies?

The FUND case study in Chapter 6 found that impacts were positive over the time period in all countries and scenarios, and higher income households experienced greater absolute impacts in all cases. The distribution of proportional impacts, however, varied across countries. In Ethiopia and India, for example, lower expenditure or income quintiles always saw greater percentage impacts, while the opposite was true in Mexico and Zambia. A slightly less clear pattern was observed in the US, where, generally, higher income quintiles experienced greater impacts; although proportional impacts in all scenarios started off more skewed towards the third versus the fourth quintile, with this skew switching to the opposite as time progressed. Similarly, in Vietnam, lower expenditure quintiles saw greater impacts in A2 and B1, and at the start of A1B and B2; however, in the latter two scenarios, the opposite became true over time. Finally, the ranking of proportional impacts across household groups in Egypt displayed no clear pattern, with rankings changing across scenarios and time.

In the Alaskan case study, low-income households experienced the smallest effects in absolute terms across impacts from all sectors. Meanwhile, high-income households experienced the largest absolute impacts from projected changes to fisheries and oil extraction, and middle-income households experienced the largest absolute impacts from projected changes to tourism and spending on infrastructure repairs. In percentage terms, however, lower income households consistently did least well across all sectors, as this group saw the highest percentage impacts for the negative income effects from increased infrastructure repair costs, and the lowest percentage impacts for the positive income effects from increased tourism, and fishing and oil outputs. High income households enjoyed the greatest proportional benefits from increased fishing and oil outputs, while middle income households benefited the most, relatively speaking, from tourism.

The results from this thesis, thus, do not support a simple narrative, such as 'climate change will always hit the poor the hardest'. While the Alaska case study and the Mexican and Zambian results from the FUND case study demonstrate that the poor could do least well out of climate change, the results from Ethiopia and India in the FUND case study conversely show that it is also plausible that the poor could benefit most from a warmer world. Although had the FUND case study been run over a longer time period, the benefits of warming would have been outweighed by the costs of warming, and households that had been seeing the largest proportional increases in income could then find themselves, in relative terms, suffering the most.

### 8.1.4 Is there evidence to support the conclusion in Rozenberg and Hallegatte (2015) that starting levels of average income and within-country income inequality may affect the extent that climate change impacts on inequality?

Using Pearson correlation coefficients[128], let us first examine if impacts from exogenous unit changes to sectors[129] differed linearly according to starting inequality ratios and average income. Low, moderate and high correlations were defined to be correlation coefficients with absolute values below 0.4, from 0.4 to 0.6, and above 0.6 respectively. As one can see from Table 8.2, no moderate or strong correlation could be found between the changes in inequality ratios and starting incomes, as no correlation coefficient had an absolute value greater than 0.4.

In contrast, the linear correlations between the effects on inequality ratios of unit exogenous increases of each given sector and starting levels of inequality were frequently high; although, sometimes they were moderate or low. Impacts from a unit change in water utilities output on inequality ratios were strongly positively correlated with all baseline inequality ratios. In other words, more unequal countries typically saw greater increases in inequality from a unit increase in water output, and inequality ratios even slightly decreased in Egypt, the most equal country. Meanwhile, impacts from unit changes in expenditure on energy and repairing storm damages were also strongly positively correlated with all baseline inequality ratios, except Q3/Q1, where the correlations were only weak. For a unit increase in energy expenditure, more unequal countries typically saw greater increases in inequality, with India, one of the more equal countries even seeing small decreases in inequality ratios. Similarly, for a unit increase in expenditure on repairing storm

[128] The Pearson correlation coefficient is the ratio of the covariance of two variables to the product of their standard deviations. This ratio can vary between -1 and 1, which represent total negative and positive linear correlations respectively. When a correlation coefficient is equal to zero, this means there is no linear correlation between the variables.

[129] Impacts from exogenous unit changes were calculated in Section 8.1.1 of this chapter, using an IOA of each country's SAM, and were detailed in Figure 8.3. None of the sectors or household groupings in the Alaska and FUND case studies overlapped, so the Alaska case study could not be included in this analysis.

damages, more unequal countries typically saw greater increases in inequality, with many of the more equal countries instead seeing small decreases in inequality ratios. Agriculture was strongly negatively correlated with all baseline inequality ratios, except Q3/Q1, where the correlations were only weak. So more unequal countries typically saw greater reductions in inequality; although the US and Mexico saw very small increases in inequality ratios. Finally, impacts on inequality ratios from a unit change in expenditure on coastal protection were weakly correlated with all inequality ratios, except Q5/Q3, where there was a moderate positive correlation; that is, more equal countries typically saw greater decreases in this inequality ratio.

Table 8.2 – Correlations between impacts on inequality ratios from unit exogenous increases to sectors and 2017 GDP per capita and starting inequality ratios

| **Sector subject to an exogenous unit increase** | **Correlation between impact on Q5/Q1 and 2017 GDP per capita (in USD)** | **Correlation between impact on Q5/Q3 and 2017 GDP per capita (in USD)** | **Correlation between impact on Q3/Q1 and 2017 GDP per capita (in USD)** | **Correlation between impact on (Q4+Q5)/(Q1+Q2) and 2017 GDP per capita (in USD)** | **Correlation between impact on Q5/Q1 and baseline Q5/Q1** | **Correlation between impact on Q5/Q3 and baseline Q5/Q3** | **Correlation between impact on Q3/Q1 and baseline Q3/Q1** | **Correlation between impact on (Q4+Q5)/(Q1+Q2) and baseline (Q4+Q5)/(Q1+Q2)** |
|---|---|---|---|---|---|---|---|---|
| Agriculture | 0.33 | 0.31 | 0.38 | 0.32 | -0.69 | -0.81 | -0.09 | -0.77 |
| Water | -0.32 | -0.33 | -0.32 | -0.32 | 0.67 | 0.64 | 0.71 | 0.70 |
| Energy | -0.32 | -0.33 | -0.32 | -0.32 | 0.70 | 0.78 | 0.16 | 0.76 |
| SLR | 0.34 | 0.32 | 0.35 | 0.34 | 0.28 | 0.43 | 0.14 | 0.27 |
| Storms | -0.24 | -0.24 | -0.24 | -0.24 | 0.66 | 0.65 | 0.19 | 0.71 |

Notes: Table shows the Pearson correlation coefficients of impacts on four inequality ratios from exogenous unit increases to five sectors in the seven countries featuring in the FUND case study, and 2017 GDP per capita, in USD, and starting inequality ratios in those countries. The four inequality ratios are Q5/Q1, Q5/Q3, Q3/Q1 and (Q4+Q5)/(Q1+Q2). Q1 represents the income of the lowest expenditure or income quintile, while Q5 represents the income of highest expenditure or income quintile. Income quintiles were used for Mexico and the US, while expenditure quintiles were used for Egypt, Ethiopia, India, Vietnam and Zambia. Correlation coefficients can vary between -1 and 1, which represent total negative and positive linear correlations respectively. When a correlation coefficient is equal to zero, this means there is no correlation between the variables. Unit exogenous increases were explored for five sectors: agricultural output, water utilities output, expenditure on energy, expenditure on coastal defence from SLR, and expenditure on repairing damages from storms. The impacts of unit changes were taken from Figure 8.3 in this chapter, while 2017 GDP per capita, in USD, were taken from Table 3.2 in Chapter 3. Baseline inequality ratios were calculated from the relevant countries' SAMs.

These results suggest that more unequal countries could generally experience greater changes in inequality ratios than their more equal counterparts. Whether this occurs, however, is dependent on if there is a correlation between the size of exogenous increases to sectors and starting levels of inequality. To assess this, Pearson correlations were explored between the largest percentage changes in a given inequality ratio that were observed for each sector in each country in the FUND case study[130], and starting inequality ratios and average income. These correlation coefficients are shown in Table 8.3.

Table 8.3 – Correlations between largest percentage changes in inequality ratios from exogenous changes to given sectors that were observed in any scenario at any point during the FUND case study and 2017 GDP per capita and starting inequality ratios

| **Sector subject to an exogenous unit increase** | **Correlation between impact on Q5/Q1 and 2017 GDP per capita (in USD)** | **Correlation between impact on Q5/Q3 and 2017 GDP per capita (in USD)** | **Correlation between impact on Q3/Q1 and 2017 GDP per capita (in USD)** | **Correlation between impact on (Q4+Q5)/(Q1+Q2) and 2017 GDP per capita (in USD)** | **Correlation between impact on Q5/Q1 and baseline Q5/Q1** | **Correlation between impact on Q5/Q3 and baseline Q5/Q3** | **Correlation between impact on Q3/Q1 and baseline Q3/Q1** | **Correlation between impact on (Q4+Q5)/(Q1+Q2) and baseline (Q4+Q5)/(Q1+Q2)** |
|---|---|---|---|---|---|---|---|---|
| Agriculture | 0.36 | 0.36 | 0.35 | 0.36 | 0.34 | 0.34 | 0.21 | 0.32 |
| Energy | -0.32 | -0.33 | -0.30 | -0.32 | 0.19 | 0.28 | -0.01 | 0.26 |
| SLR | 0.30 | 0.30 | 0.31 | 0.30 | 0.24 | 0.42 | 0.08 | 0.23 |
| Storms | 0.87 | -0.94 | 0.98 | 0.80 | 0.90 | 0.15 | 0.98 | 0.85 |

Notes: Table shows the Pearson correlation coefficients between the largest percentage changes in four inequality ratios that were observed in any scenario at any point during the FUND case study, due to FUND-estimated exogenous changes to given sectors, and 2017 GDP per capita, in USD, and the four starting inequality ratios, in the seven countries in the FUND case study. The four inequality ratios are Q5/Q1, Q5/Q3, Q3/Q1 and (Q4+Q5)/(Q1+Q2). Q1 represents the income of the lowest expenditure or income quintile, while Q5 represents the income of highest expenditure or income quintile. Income quintiles were used for Mexico and the US, while expenditure quintiles were used for Egypt, Ethiopia, India, Vietnam and Zambia. Correlation coefficients can vary between -1 and 1, which represent total negative and positive linear correlations respectively. When a correlation coefficient is equal to zero, this means there is no correlation between the variables. Exogenous changes were explored for four sectors: agricultural output, water utilities output, expenditure on energy, expenditure on coastal defence from SLR, and expenditure on repairing damages from storms. Exogenous changes to water output were excluded from this analysis, as they were from the FUND case-study, due to the concerns raised in Chapter 6 about the calibration of the water impact functions. The largest percentage changes were taken from Table 8.1 in this chapter, while 2017 GDP per capita, in USD, were from Table 3.2 in Chapter 3. Baseline inequality ratios were calculated from the relevant countries' SAMs.

One can see that for exogenous changes to agriculture and energy sectors, there were only low correlations between impacts on inequality ratios and 2017 GDP per capita, in USD, and baseline inequality ratios in the countries. The same was true for impacts from exogenous increases in construction for repairing storm damages, with the exception of the correlation between impacts on

[130] These percentage changes were detailed earlier in this chapter, in Table 8.1.

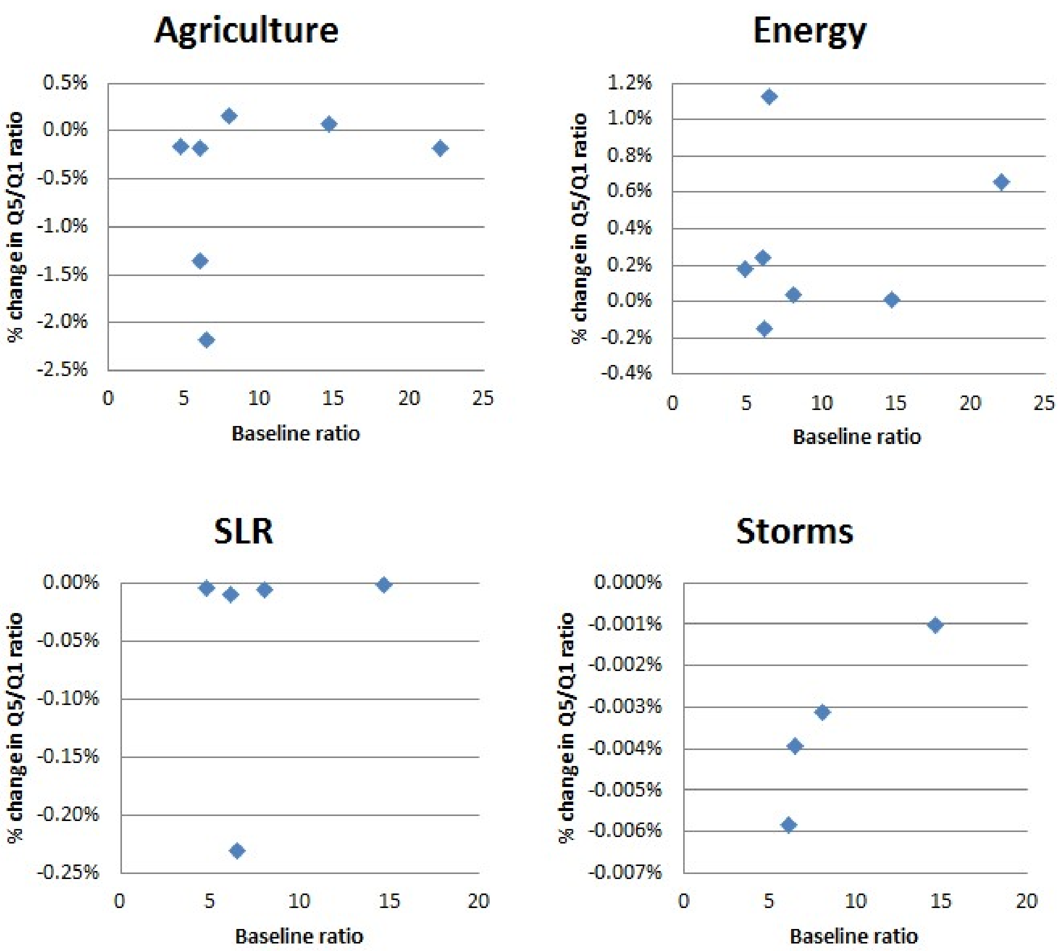
the Q5/Q3 ratio and baseline Q5/Q3 ratios, where there was a moderate correlation. This correlation, however, was 0.42, and so was only just over the threshold to be classified as moderate. Finally, very strong correlations were typically observed between impacts from exogenous increases in construction for building coastal defences and both starting levels of inequality and income, with correlation coefficients ranging from 0.80 to 0.98. The exception was the correlation between impacts on the Q5/Q3 ratio and baseline Q5/Q3 ratios, where there was a very weak correlation of 0.15.

Thus, with the exception of expenditure on repairing storm damages, no convincing correlations were found between the maximum changes in inequality ratios in the FUND case study and starting levels of income and inequality ratios. The absence of correlations with FUND's estimated exogenous changes thus outweighed the correlations between impacts from unit exogenous increases in sectors and starting levels of inequality. For example, maximum changes in inequality ratios from FUND's estimated exogenous increases in expenditure on repairing storm damages were typically strongly correlated with starting levels of income and inequality ratios, despite impacts on inequality ratios from a unit change in expenditure on coastal protection having no convincing correlation with starting incomes or inequality.

To illustrate the correlations, Figure 8.5 shows scatter plots of the baseline Q5/Q1 ratios versus the largest percentage changes in the Q5/Q1 ratios that were observed in each country in the FUND case study, due to exogenous changes in each sector. While these plots are for the Q5/Q1 ratio, very similar patterns were observed for other ratios. One can clearly see that the only convincing correlation is with impacts from repairing storm damages.

In short, the correlations between the effects on inequality ratios of unit exogenous increases of each given sector and starting levels of inequality were frequently high, which suggests there is potential for starting levels of within-country income inequality to affect the extent that climate change impacts on inequality. The results from the FUND case study, however, demonstrate that these correlations play only a very small role. The correlations, or lack thereof, between the scale of exogenous impacts and starting levels of inequality were far more influential.

Figure 8.5 – Baseline Q5/Q1 ratios versus maximum percentage changes in Q5/Q1 ratios in the seven countries in the FUND case study, broken down according to the sector exogenously driving changes




Notes: Figure plots the largest percentage changes in the Q5/Q1 inequality ratios that were observed in any of the four scenarios and at any point in time for each of the seven countries in the FUND case study detailed in Chapter 6, against baseline inequality ratios, i.e. initial inequality ratios calculated from the relevant countries' SAMs. Q1 represents the income of the lowest expenditure or income quintile, while Q5 represents the income of highest expenditure or income quintile. Mexico and the US used income quintiles, while all other countries used expenditure quintiles. The percentage changes were driven by climate change impacts on four economic sectors, agricultural output, energy demand, coastal defence expenditure from sea-level rise (SLR), and expenditure on repairing economic damages from tropical and extratropical storms. Changes driven by impacts to each of the four sectors are shown in separate graphs. In each graph, there is a separate data point for each country. Changes from impacts on coastal defence expenditure were not modelled for Ethiopia or Zambia, as these countries are landlocked. Positive (negative) changes indicate increases (decreases) in the relevant inequality ratio. One can see that, with the exception of impacts from repairing storm damages, no convincing correlations can be found. Correlation coefficients are 0.34, 0.19, 0.24 and 0.90 for agriculture, energy, SLR and storms respectively.

### 8.1.5 Are within-country income inequality effects relatively small in many or all scenarios compared to projected growth in average income? Alternatively, is it possible, as suggested by Dennig et al. (2015) and Rozenberg and Hallegatte (2015), that increased inequality from climate change might cancel out improvements in overall standards of living from GDP growth for low-income households?

To explore this question, a new ratio, $YoY^{(u)}{}_t$, was introduced to see cumulative climate impacts incurred in $t$ as percentages of the exogenous year-on-year (YoY) growth in incomes between $t-1$ and $t$. Using the variables and notation defined in Chapter 6, as the economy of a given country in a given scenario grew by $\gamma_t = (1 + g_t)$ between $t-1$ and $t$,

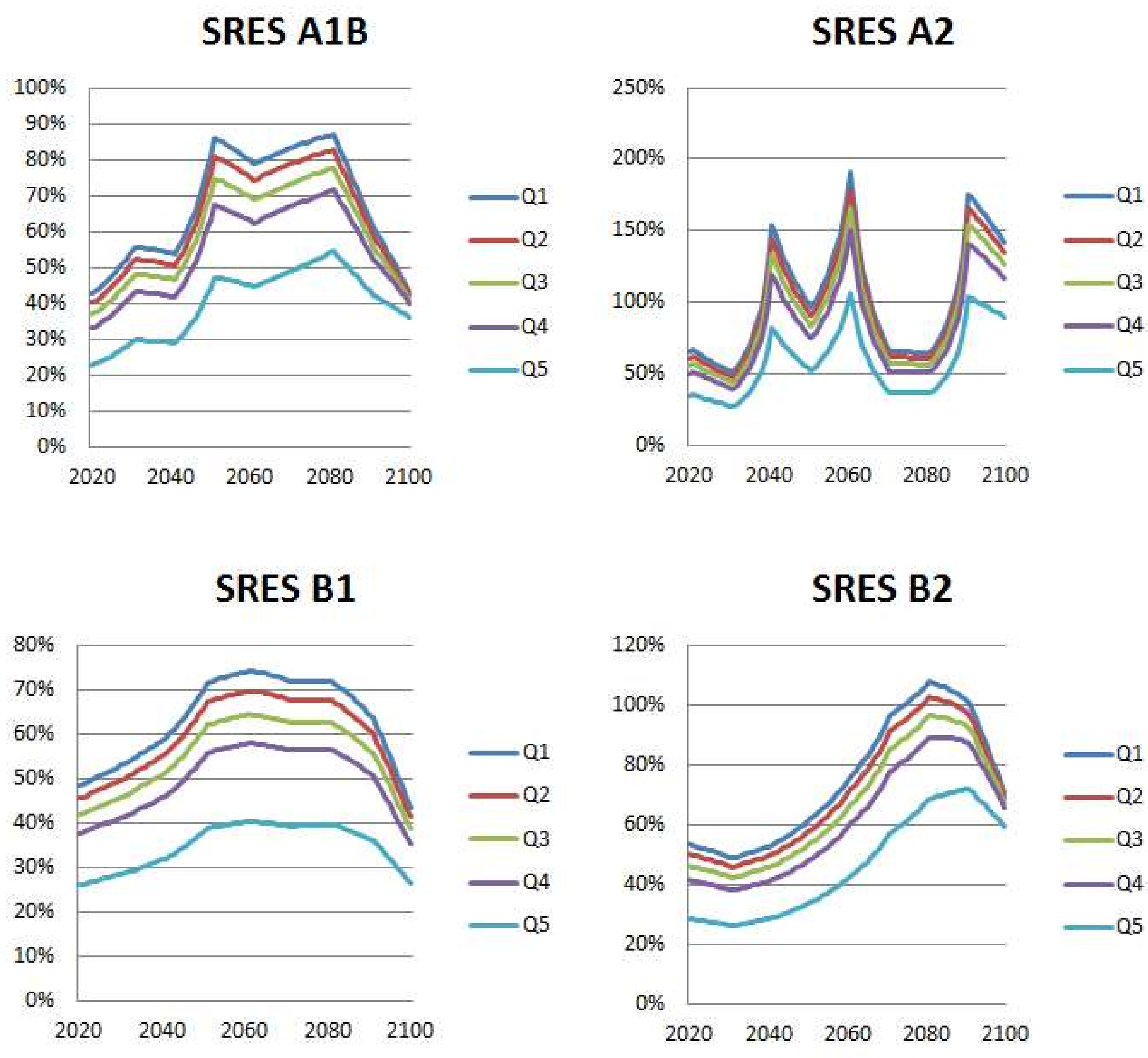
$$YoY^{(u)}{}_t = \frac{\Delta x^{(u)}{}_t}{g_t \tilde{x}^{(u)}{}_{t-1}}.$$

This ratio captured the proportion of the most recent YoY exogenous growth in income that was gained or lost at time $t$ due to cumulative climate change impacts. For example, if $YoY^{(u)}{}_t = -1$, i.e. $\Delta x^{(u)}{}_t = -g_t \tilde{x}^{(u)}{}_{t-1}$, this would mean that all of the most recent YoY exogenous growth in baseline income had been negated by the cumulative climate change impacts at $t$. While, as detailed in Chapter 6, all net cumulative impacts in the FUND case study were positive, and so could not possibly cancel out the effects of positive growth, it was still interesting to compare the magnitude of the impacts generated by FUND with YoY growth, to assess the scale of the estimates.

For the FUND case study results, the pattern the $YoY^{(u)}{}_t$ percentage followed over time varied by country and scenario, with YoY percentages sometimes falling with time, sometimes rising to a peak and then falling, sometimes continuously rising, and other times fluctuating throughout the time period. As an example, Figure 8.6 shows YoY ratios for Ethiopian household groups in the four SRES scenarios.

Table 8.4 shows how the maximum $YoY^{(u)}{}_t$ percentage observed over the time period varied by household group, country and scenario, and the range of these maximum percentages observed across the household groups for each country and scenario. One can see that the maximum cumulative impacts, as a percentage of the most recent exogenous YoY growth in incomes, differed greatly across countries and scenarios, as did the range observed across household groups. In addition, which household groups experienced the largest cumulative impacts, as percentages of YoY growth, differed from country to country and, in the case of Egypt, across scenarios. These differences naturally mirrored the distribution of cumulative changes in incomes across household groups, as percentages of counterfactual baseline incomes, which were observed in Chapter 6.

Figure 8.6 – Ethiopian cumulative climate impacts incurred each year, as percentages of the most recent exogenous year-on-year (YoY) growth in incomes, in four SRES scenarios, for each household expenditure quintile




Notes: Figure shows, for Ethiopia, the cumulative total changes in household expenditure quintiles' incomes at each point in time between 2020 and 2100, in each scenario, SRES A1B, A2, B1 and B2, as percentages of exogenous YoY income growth for the relevant quintile. A separate graph is shown for each scenario. Q1 represents the income of the lowest expenditure quintile, while Q5 represents the income of highest expenditure quintile. The cumulative changes were driven by climate change impacts on four economic sectors, agricultural output, energy demand, coastal defence expenditure from sea-level rise (SLR), and expenditure on repairing economic damages from tropical and extratropical storms, but were modelled together to give cumulative total changes.

All FUND-estimated total impacts were positive across all countries and scenarios. This naturally resulted in all $YoY^{(u)}{}_t$ percentages being positive, so YoY exogenous growth couldn't even be partly negated by climate change impacts. These positive impacts were primarily down to sizable projected agricultural benefits from $CO_2$ fertilisation and the level of climate change; although, agricultural benefits diminished but didn't turn negative by the end of the time period. However, if FUND's impact functions were overly optimistic about these effects, which some argue, for example, see Ackerman and Munitz (2012), than total impacts across all sectors could swiftly turn negative. It was, thus, still interesting to explore the scale of the estimates by comparing the magnitudes of the impacts generated by FUND with YoY growth.

The largest cumulative impact, as a percentage of the most recent YoY exogenous growth in income, was observed for Q1 in Vietnam in SRES A2, and amounted to nearly three years of exogenous growth, with all other quintiles seeing maximum cumulative impacts that amounted to 174% to 264% of the most recent YoY exogenous growth. Quintile impacts in Vietnam in SRES A1B and B2 were, respectively, equivalent to approximately one and two years of exogenous YoY growth, while cumulative quintile impacts in SRES B1 ranged from 57% to 112% of the most recent YoY exogenous growth. Egyptian quintiles in A1B, A2 and B2, saw cumulative impacts that amounted to 100 to 200% of the most recent YoY exogenous growth. Similar sized effects were seen for all quintiles in Ethiopia in A2. While the two poorest Ethiopian quintiles and two wealthiest Zambian quintiles in B2 saw impacts approximately equivalent to the most recent YoY exogenous growth. There is thus evidence to suggest that climate change could conceivably negate a few years of exogenous growth. Effects in India, Mexico and the US, however, were smaller with cumulative impacts never respectively exceeding 89%, 54% and 23% for any quintile in any scenario. Even if FUND estimated total impacts were negative instead of positive, such impacts wouldn't erode even one year of exogenous growth.

Table 8.4 – Maximum percentage of the most recent YoY exogenous growth in income that was gained or lost, due to cumulative climate change impacts, in any year during the time period, broken down by country, scenario and household group

| **Country** | **Scenario** | **Q1** | **Q2** | **Q3** | **Q4** | **Q5** | **Range (in percentage points)** |
|---|---|---|---|---|---|---|---|
| Egypt | A1B | 111% | 113% | 113% | 112% | 114% | 3 |
| | A2 | 194% | 197% | 196% | 194% | 196% | 3 |
| | B1 | 66% | 67% | 66% | 65% | 65% | 2 |
| | B2 | 170% | 174% | 175% | 174% | 178% | 9 |
| Ethiopia | A1B | 87% | 83% | 78% | 72% | 54% | 32 |
| | A2 | 191% | 179% | 166% | 150% | 106% | 85 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | B1 | 74% | 70% | 64% | 58% | 40% | 34 |
| | B2 | 107% | 102% | 96% | 89% | 72% | 36 |
| India | A1B | 40% | 37% | 35% | 33% | 30% | 9 |
| | A2 | 89% | 84% | 81% | 78% | 72% | 17 |
| | B1 | 35% | 33% | 32% | 31% | 28% | 6 |
| | B2 | 68% | 63% | 60% | 56% | 51% | 17 |
| Mexico | A1B | 19% | 19% | 19% | 20% | 23% | 5 |
| | A2 | 43% | 43% | 44% | 45% | 54% | 11 |
| | B1 | 16% | 16% | 16% | 17% | 20% | 4 |
| | B2 | 22% | 22% | 22% | 23% | 29% | 7 |
| USA | A1B | 5% | 7% | 8% | 8% | 10% | 5 |
| | A2 | 12% | 15% | 18% | 17% | 22% | 10 |
| | B1 | 11% | 14% | 16% | 16% | 19% | 9 |
| | B2 | 13% | 16% | 20% | 18% | 23% | 10 |
| Vietnam | A1B | 130% | 122% | 114% | 107% | 96% | 35 |
| | A2 | 294% | 264% | 231% | 199% | 174% | 120 |
| | B1 | 112% | 100% | 87% | 74% | 57% | 55 |
| | B2 | 214% | 202% | 194% | 203% | 208% | 20 |
| Zambia | A1B | 39% | 42% | 47% | 56% | 65% | 27 |
| | A2 | 71% | 76% | 85% | 95% | 108% | 37 |
| | B1 | 22% | 24% | 25% | 28% | 30% | 8 |
| | B2 | 67% | 74% | 85% | 101% | 118% | 51 |

Notes: Table shows, for each of the seven countries in the FUND case study, the maximum percentage of exogenous year-on-year (YoY) income growth that was gained as a result of climate change impacts, at any point in time between 2020 and 2100, for each household expenditure or income quintile. Climate change impacts on four economic sectors were considered: agricultural output, energy demand, coastal defence expenditure from sea-level rise (SLR), and expenditure on repairing economic damages from tropical and extratropical storms. The cumulative changes to the four sectors were modelled together to give cumulative total changes. Note that these total changes were positive in all cases, as FUND estimates large agricultural benefits from climate change. Results are given for each of the four scenarios, SRES A1B, A2, B1 and B2, and for each household quintile. Q1 represents the income of the lowest expenditure or income quintile, while Q5 represents the income of highest expenditure or income quintile. Mexico and the US used income quintiles, while all other countries used expenditure quintiles. The greatest difference in these maximum percentages observed across quintiles in each country and scenario is also given in the table, in percentage points, in the column titled ‘Range’.

Table 8.5 – Percentage of the most recent YoY exogenous growth in income that was gained or lost due to cumulative climate change impacts, broken down by sector, scenario and household group

| | | | **Infrastructure** | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Fisheries** | | **RCP 4.5** | | **RCP 8.5** | | | **Tourism** | | |
| | **Without ocean acidification** | **With ocean acidification** | **Without adaptation** | **With adaptation** | **Without adaptation** | **With adaptation** | **Oil** | **SRES A2** | **SRES B1** | **SRES B2** |
| **L** | 70% | 68% | -1431% | -536% | -215% | -82% | 184% | 42% | 86% | 113% |
| **M** | 147% | 144% | -1226% | -458% | -184% | -70% | 551% | 83% | 169% | 223% |
| **H** | 330% | 322% | -621% | -228% | -92% | -34% | 739% | 60% | 120% | 158% |

Notes: Table shows the maximum percentage of exogenous year-on-year (YoY) income growth that was gained or lost as a result of climate change impacts, over the time period covered in the case study detailed in Chapter 7, for each Alaskan household income group. H represents the total income of high income households (households earning more than $75,000 a year, in 2008 USD), M represents the total income of medium income households (households earning between $25,000 and $75,000 a year, in 2008 USD), and L represents the total income of low income households (households earning less than $25,000 a year, in 2008 USD). Climate change impacts on four economic sectors were considered: fisheries output, oil industry output, spending by tourists, and expenditure on infrastructure (road, buildings, airports, railroads, and pipelines) repairs after damage from flooding, permafrost thaw, precipitation and freeze-thaw dynamics. Changes driven by impacts to each of the four sectors are shown separately. As described in Chapter 7, one scenario was used for impacts to the oil industry, two scenarios, with and without ocean acidification, were used for changes to fisheries, four scenarios, RCPs 4.5 and 8.5, both with and without adaptation, were used for changes to infrastructure, and three scenarios, SRES A2, B1 and B2 were used for changes to tourism. The results from these different scenarios are all shown separately.

The $YoY^{(u)}{}_t$ percentages observed in the Alaska case study were generally much larger than those observed in the FUND case study. Table 8.5 details the percentages for each household group, sector and scenario. As was seen in Chapter 7, the impacts from all sectors, except infrastructure, were positive and so reinforced YoY growth. The impacts from infrastructure were negative and, at times, particularly large, negating up to over 14 times the most recent year's exogenous YoY growth. In some scenarios, however, impacts were more modest, for example, in RCP 8.5 with adaptation, cumulative costs from infrastructure expenditure never amounted to more than 34% of the most recent exogenous YoY income growth. Cumulative impacts from changes to oil output were also large, ranging from 184 to 739% of the most recent exogenous YoY income growth. Cumulative impacts from changes to fisheries output were typically smaller, as they spanned 68 to 330% of the most recent exogenous YoY income growth. This was a similar range to that observed for Vietnam in the FUND case study, i.e. the largest cumulative impacts in the FUND case study. Finally, the magnitudes of cumulative Alaskan impacts were typically smallest when generated by changes in tourism. These were, however, still comparable in size to those typically observed in the FUND case study, as they ranged from 42% to 158% of the most recent exogenous YoY income growth.

Once again, the distribution of cumulative impacts, as percentages of YoY growth, across household groups naturally mirrored the distribution of cumulative changes in incomes across household groups, as percentages of counterfactual baseline incomes, which were observed in Chapter 7.

It must be emphasised that the impacts used to estimate the YoY percentages in both case studies were *cumulative* impacts, and that these were being compared to exogenous average income growth from just one year to the next. If it would take cumulative impacts many years to negate growth over just one year, or over a relatively small number of years, then this suggests that the *cumulative* impacts of climate change on household incomes are unlikely to significantly diminish the benefits of *cumulative* exogenous growth in average incomes. Despite the variety of maximum ${YoY^{(u)}}_t$ percentages observed across countries and scenarios in the FUND case study, the largest observed was still only 294%. Three times the most recent exogenous year-on-year (YoY) growth in incomes is, arguably, not a large cost from cumulative impacts from climate change that have built up over many years. Similarly, while costs of over 14 times the most recent year's exogenous YoY growth were generated for Alaska from infrastructure, these cumulative effects occurred in 2099. These 14 to 15 years of lost growth would be more than compensated for by many preceding decades of growth. The results of this thesis thus do not support the suggestion in Dennig et al. (2015) and Rozenberg and Hallegatte (2015) that climate change may disrupt the notion that 'growth is good for the poor', even though growth is driving climate change.

### 8.1.6 Is it only in the most extreme climate damage scenarios and time frames that relatively sizable inequality effects emerge? Or are they plausible in shorter-term, moderate scenarios?

Table 8.6 shows the largest percentage cumulative changes in inequality ratios for each inequality ratio observed across all scenarios for each country in the FUND case study. The cumulative changes appear small, as no ratio changed from its baseline by more than 0.14%, 1.22%, 0.24%, 0.16%, 0.08%, 2.33% and 0.61% for Egypt, Ethiopia, India, Mexico, the US, Vietnam and Zambia respectively.

Table 8.6 – Largest changes in each inequality ratio, as percentages of baseline inequality ratios, observed in the FUND case study across all scenarios, broken down by country

| Country | Inequality ratio | Largest observed percentage change in inequality ratio |
|---|---|---|
| Egypt | Q5/Q1 | 0.14% |
| | Q5/Q3 | 0.06% |
| | Q3/Q1 | 0.08% |
| | (Q4+Q5)/(Q1+Q2) | 0.08% |
| Ethiopia | Q5/Q1 | -1.22% |
| | Q5/Q3 | -0.87% |
| | Q3/Q1 | -0.35% |
| | (Q4+Q5)/(Q1+Q2) | -0.93% |
| India | Q5/Q1 | -0.24% |
| | Q5/Q3 | -0.12% |
| | Q3/Q1 | -0.12% |
| | (Q4+Q5)/(Q1+Q2) | -0.17% |
| Mexico | Q5/Q1 | 0.16% |
| | Q5/Q3 | 0.15% |
| | Q3/Q1 | 0.01% |
| | (Q4+Q5)/(Q1+Q2) | 0.13% |
| USA | Q5/Q1 | 0.08% |
| | Q5/Q3 | 0.07% |
| | Q3/Q1 | 0.05% |
| | (Q4+Q5)/(Q1+Q2) | 0.05% |
| Vietnam | Q5/Q1 | -2.33% |
| | Q5/Q3 | -1.29% |
| | Q3/Q1 | -1.05% |
| | (Q4+Q5)/(Q1+Q2) | -1.79% |
| Zambia | Q5/Q1 | 0.61% |
| | Q5/Q3 | 0.39% |
| | Q3/Q1 | 0.22% |
| | (Q4+Q5)/(Q1+Q2) | 0.51% |

Notes: Table shows, for each country in the FUND case study, the largest percentage change observed in each of the four inequality ratios, Q5/Q1, Q5/Q3, Q3/Q1, and (Q4+Q5)/(Q1+Q2), in the FUND case study. Q1 represents the income of the lowest expenditure or income quintile, while Q5 represents the income of highest expenditure or income quintile. Mexico and the US used income quintiles, while all other countries used expenditure quintiles. Percentages represent deviations from counterfactual baseline ratios. Counterfactual baseline ratios were calculated from the SAMs, and so they assume no effects from climate change. Positive (negative) changes indicate increases (decreases) in the relevant inequality ratio. Data on largest observed percentage changes were taken from Tables 6.2 to 6.8 in Chapter 6.

To help define a 'relatively sizable' change in inequality, historical standard deviations of the four inequality ratios were calculated for each country in the FUND case study using World Bank time series on income quintiles' shares of total household income (World Bank, 2019b). The largest cumulative change observed in each inequality ratio for each country in the FUND case study was then compared to the standard deviation of historical changes in the relevant ratio generated from the World Bank time-series. This gave a measure of whether the inequality impacts generated by climate change were comparable in magnitude to fluctuations in inequality in recent memory.

The results are displayed in Table 8.7. In all countries except Vietnam, which typically saw the largest proportional impacts in the FUND case study, the maximum magnitudes of changes in inequality ratios amounted to only small percentages of historical standard deviations of inequality ratios. Specifically, never more than 3%, 5%, 6%, 2%, 2% and 4% for Egypt, Ethiopia, India, Mexico, the US, and Zambia respectively. Thus, even over eighty-years, let alone a shorter time-scale, FUND-estimated cumulative impacts on income inequality, for most countries, typically looked fairly small compared to recent changes in inequality that were unrelated to climate change.

For Vietnam, changes to inequality ratios were equivalent to up to 41% of historical standard deviations. Thus, if a Vietnamese inequality ratio were to change by 2.33%, this could feel more significant to the population than one might anticipate, as such a change would be equivalent to approximately two fifth of the standard deviation of inequality ratios since 1992. Nevertheless, it would not represent a dramatic change in inequality, particularly as inequality ratios in Vietnam have not historically experienced large fluctuations[131].

Impacts on inequality ratios were often larger in the Alaskan case study, with ratios changing by maximums of 5.28%, 3.63%, 7.64% and 0.90% as a result of exogenous changes to infrastructure spending, fisheries output, oil output and tourism respectively. Moreover, these are impacts due to exogenous changes to individual sectors, with those from infrastructure, oil and fisheries all changes to the H/L ratio. This implies that the H/L ratio could increase by 16.55% if the relevant changes to these three sectors were to occur together. This could easily represent a sizable change; however, as historical income-inequality ratios for these household groupings could not be found for Alaska, it was not possible to compare these changes with historical standard deviations. This was disappointing, as it is plausible that these larger proportional impacts could have been comparable in magnitude to, or even possibly exceeded, fluctuations in inequality in recent memory.

[131] The historical relative standard deviations, i.e. ratios of standard deviations to means, for Vietnamese inequality ratios were 0.07, 0.06, 0.07 and 0.05 for the Q5/Q1, Q5/Q3, Q3/Q1 and (Q4+Q5)/(Q1+Q2) ratios respectively, which are all low variance.

Table 8.7 – Largest absolute changes in each inequality ratio, as percentages of the historical standard deviations of each ratio, observed in the FUND case study across all scenarios, broken down by country

| **Country** | **Years covered by time-series** | **Inequality ratio** | **Mean of historical time series** | **Standard deviation of historical time series, as a percentage of the historical mean** | **Largest absolute change observed in the FUND case study across all scenarios, as a percentage of the historical standard deviation** |
|---|---|---|---|---|---|
| Egypt | 1990 - 2015 | Q5/Q1 | 4.50 | 4.4% | 3.3% |
| | | Q5/Q3 | 2.54 | 2.9% | 2.1% |
| | | Q3/Q1 | 1.77 | 2.5% | 3.2% |
| | | (Q4+Q5)/(Q1+Q2) | 2.82 | 3.3% | 2.5% |
| Ethiopia | 1995 - 2015 | Q5/Q1 | 5.80 | 27.2% | 4.7% |
| | | Q5/Q3 | 2.84 | 20.5% | 4.4% |
| | | Q3/Q1 | 2.02 | 8.7% | 4.1% |
| | | (Q4+Q5)/(Q1+Q2) | 3.33 | 19.4% | 4.8% |
| India | 1983 - 2011 | Q5/Q1 | 5.02 | 6.1% | 4.8% |
| | | Q5/Q3 | 2.71 | 6.5% | 2.1% |
| | | Q3/Q1 | 1.85 | 2.2% | 6.0% |
| | | (Q4+Q5)/(Q1+Q2) | 3.08 | 4.6% | 4.5% |
| Mexico | 1984 - 2016 | Q5/Q1 | 11.65 | 14.1% | 0.8% |
| | | Q5/Q3 | 4.09 | 7.1% | 2.2% |
| | | Q3/Q1 | 2.84 | 8.2% | 0.1% |
| | | (Q4+Q5)/(Q1+Q2) | 5.53 | 10.4% | 0.9% |
| USA | 1979 - 2016 | Q5/Q1 | 8.50 | 9.3% | 1.4% |
| | | Q5/Q3 | 2.87 | 6.5% | 0.5% |
| | | Q3/Q1 | 2.96 | 3.9% | 1.8% |
| | | (Q4+Q5)/(Q1+Q2) | 4.24 | 6.6% | 1.0% |
| Vietnam | 1992 - 2016 | Q5/Q1 | 6.06 | 6.7% | 37% |
| | | Q5/Q3 | 2.82 | 6.0% | 21% |
| | | Q3/Q1 | 2.15 | 7.2% | 16% |
| | | (Q4+Q5)/(Q1+Q2) | 3.50 | 4.5% | 41% |

| | | | | | |
|---|---|---|---|---|---|
| Zambia | 1991 - 2015 | Q5/Q1 | 21.25 | 81.0% | 0.8% |
| | | Q5/Q3 | 4.93 | 16.4% | 3.6% |
| | | Q3/Q1 | 4.12 | 68.7% | 0.2% |
| | | (Q4+Q5)/(Q1+Q2) | 7.97 | 39.9% | 1.6% |

Notes: Table shows, for each country in the FUND case study, the historical means of the four inequality ratios, Q5/Q1, Q5/Q3, Q3/Q1, and (Q4+Q5)/(Q1+Q2), the standard deviations of the historical inequality ratio time series, expressed as percentages of the historical means, and the largest absolute changes observed in the FUND case study across all scenarios, expressed as percentages of the standard deviations of the historical inequality ratio time series. Q1 represents the income of the lowest expenditure or income quintile, while Q5 represents the income of highest expenditure or income quintile. Mexico and the US used income quintiles, while all other countries used expenditure quintiles. Historical data was taken from World Bank (2019b). Data on largest absolute changes observed in the FUND case study were taken from Table 8.1 in this chapter.

## 8.2 Sensitivity of results

To explore the sensitivity of results to uncertainty surrounding economic structures, and the sensitivity of results to differently disaggregated factor accounts in SAMs, results for the US from the FUND case study, which were generated using the 2016 US SAM, were compared to results generated using the 2003, 2010 and 2016-edu SAMs. All other aspects of the methodology remained the same, except that FUND exogenous growth rates starting from 2003, 2010 and 2016 were used as appropriate. Once again, results were run for all sectors, except water.

Figure 8.7 shows results for the B2 scenario when using the different SAMs. This is provided as an example; however, similar pictures emerged for the other scenarios. One can see that impacts across household groups, in absolute terms, followed very similar patterns when using the 2016, 2010, 2003 and 2016-edu SAMs. Impacts in all scenarios rose to a peak and then fell, or continuously increased throughout the time period. Magnitudes of impacts were closest between the 2016 and 2016-edu SAMs. In B2, for example, the average percentage difference of impacts calculated using these two SAMs amounted to 12%, 12%, 6%, 6% and 3% for impacts on Q1, Q2, Q3, Q4 and Q5 respectively. The largest percentage changes occurred for the smallest absolute impacts, as here a small absolute deviation still resulted in a sizable percentage deviation. Larger percentage changes were, however, typically observed when comparing absolute impacts calculated using the 2003 and 2010 SAMs. The average percentage difference of impacts calculated using these SAMs, compared to the 2016 SAM, amounted to 14%, 13%, 10%, 5% and 24% for impacts on Q1, Q2, Q3, Q4 and Q5 respectively when using the 2010 SAM, and 44%, 45%, 30%, 23% and 13% for impacts on Q1, Q2, Q3, Q4 and Q5 respectively when using the 2003 SAM.

When looking at impacts as percentage changes from households' baseline incomes, differences between the 2003, 2010 and 2016 SAMs become even more pronounced. Figure 8.8 gives data using SRES A1B as an example; however, the following observations also applied to the other scenarios. As one can see, the ranking of which households experienced the greatest impacts in percentage terms varied depending on whether the 2003, 2010 or 2016 SAM was used. Even when moving from using the 2016 SAM to using the 2016-edu SAM, the ranking of the third and fourth income quintiles switched. All these differences in impacts in percentage terms affected the projected changes to the four inequality ratios. When using the 2016 and 2016-edu SAMs for SRES A1B, for example, inequality increased throughout the time period according to all four ratios. When using the 2003 and 2010 SAMs, however, the Q5/Q3 ratio decreased throughout the time period, while the (Q4+Q5)/(Q1+Q2) ratio started to decrease towards the end of the time period, when using the 2003 SAM, and both the (Q4+Q5)/(Q1+Q2) and Q5/Q1 ratios started to decrease towards the end of the time period when using the 2010 SAM.

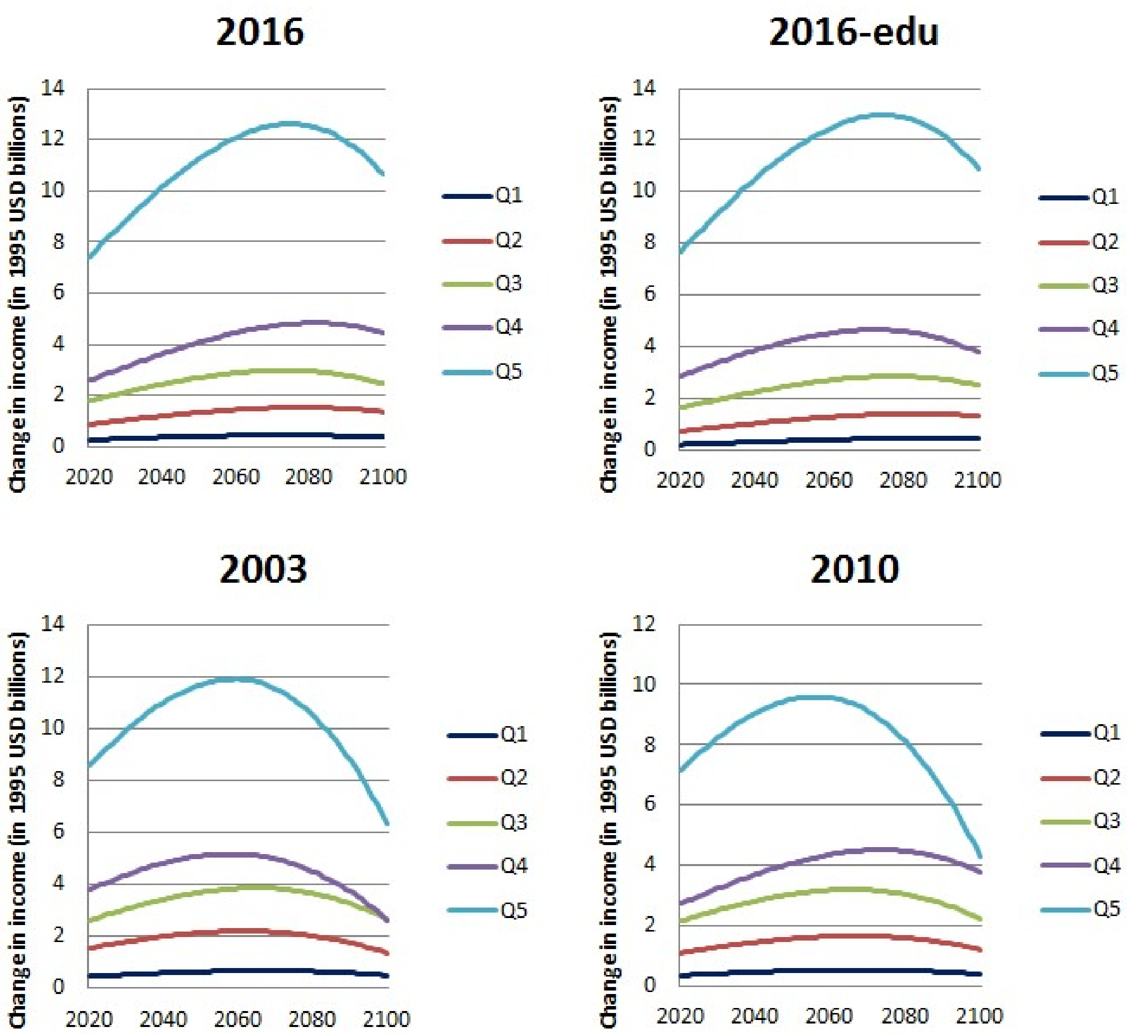
As shown in Figure 8.9, when looking at the maximum percentage changes to inequality ratios from impacts to different sectors of the economy, the pattern that agriculture produced the largest magnitude changes, significantly larger than those from other sectors, with energy, storms and SLR then producing progressively smaller results, was generally preserved. There were, however, noticeable differences between results generated using the different US SAMs; the most important being that impacts from the two most significant sectors could have different effects on inequality depending on the SAM used. For example, when using the 2003 or 2010 SAMs, the largest percentage changes in the Q5/Q3 ratio from agriculture and energy were negative, whereas when using either of the 2016 SAMs they were positive. Similarly, when using the 2003 or 2010 SAMs, the largest percentage changes in the Q5/Q1 and (Q4+Q5)/(Q1+Q2) ratios from energy were negative, whereas when using the 2016 SAM they were positive.

Thus, while many key features of results were preserved when using the different SAMs, the results of this sensitivity analysis demonstrated that changes to US economic structure, over even a short period of time, could reverse the relationship between certain sectors and measures of inequality. This reinforces the conclusion from the stability analysis in Chapter 5 that the results from this thesis should not be interpreted as predictions for any given country, but rather as an attempt to explore the range of results that could arise across economies.

While differences between results generated using the two 2016 SAMs did exist, they were typically small in comparison to those observed when using SAMs from different time periods. Nevertheless, they were sufficient to reverse the relationship between the energy sector and the Q5/Q1 and

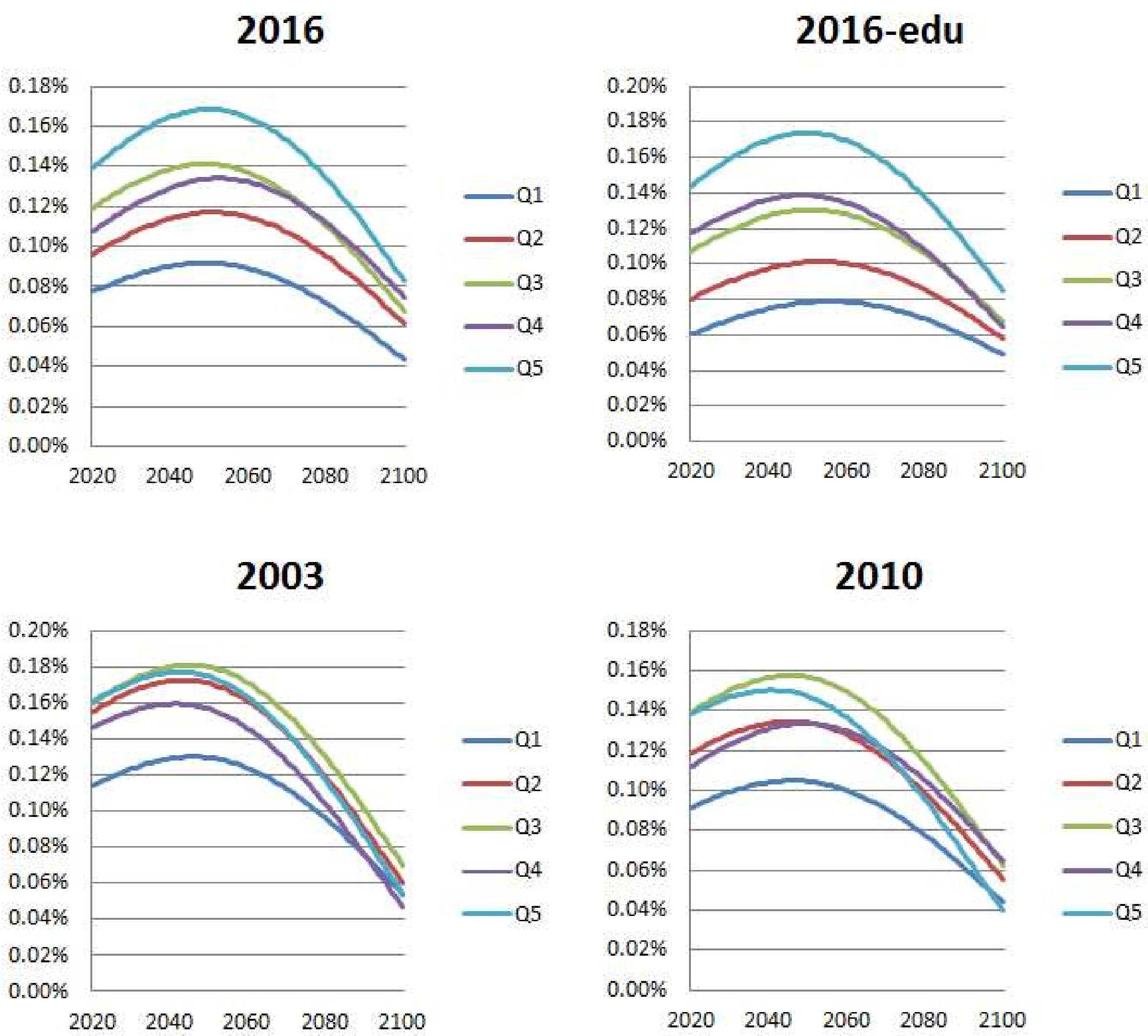
(Q4+Q5)/(Q1+Q2) inequality ratios. These both increased when using the 2016 SAM and decreased when using the 2016-edu SAM. The aggregated nature of labour accounts distinguished solely by educational level, thus, does lose information and can produce different inequality results than when using factor disaggregation that preserves industry-specific dynamics. Such aggregation biases are a common problem in input-output analysis (Miller and Blair, 2009).

Figure 8.7 – Cumulative changes (in 1995 USD billions) in US household income quintiles' incomes, from counterfactual baseline incomes, in SRES B2, when using 2003, 2010, 2016 and 2016-edu SAMs




Notes: Figure shows the cumulative changes in income for each American household income quintile as a result of FUND's estimated climate change impacts on agricultural output, energy expenditure, expenditure building coastal defences and expenditure on reconstruction after storm damages. Results are aggregated direct and indirect effects from all four sectors. The case study was run from 2020 to 2100, using the four different US SAMs constructed in Chapter 4, for 2003, 2010, 2016, and 2016-edu, where 2016-edu was an alternatively disaggregated 2016 SAM, as described in Chapter 4. Q1 represents the income of the lowest income quintile, and Q5 represents the income of highest income quintile.

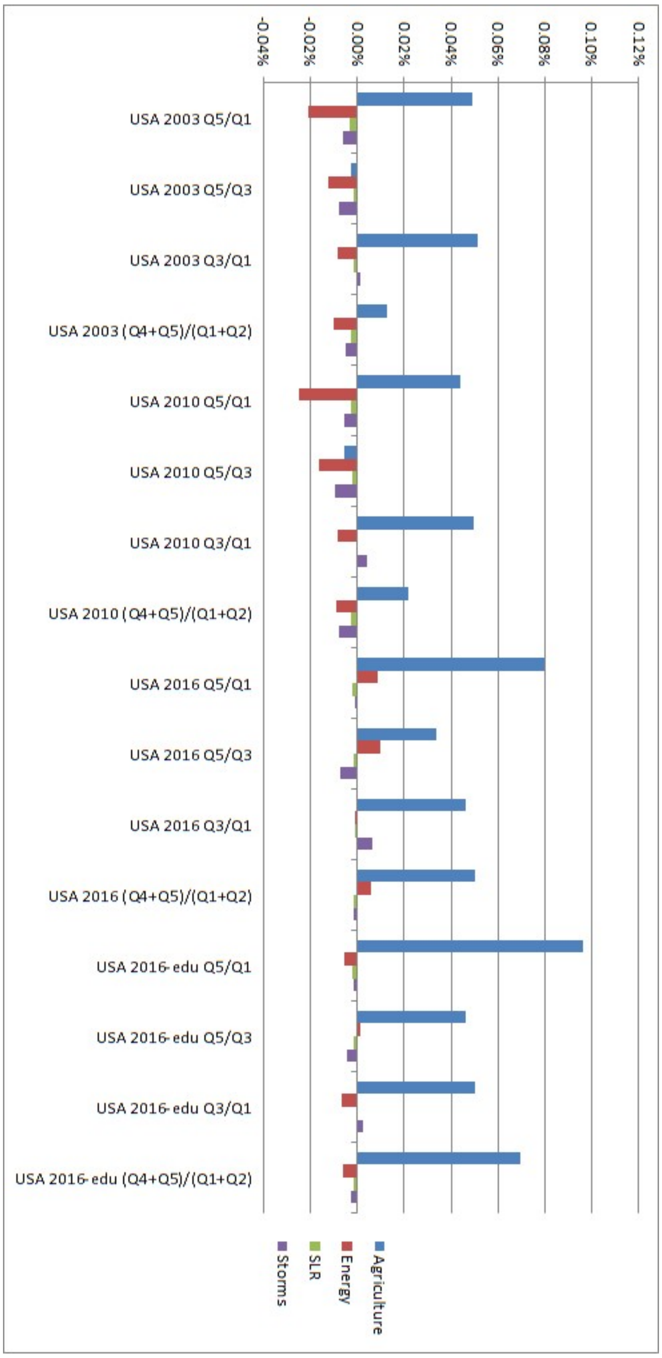
Figure 8.8 – Cumulative changes in US household income quintiles' incomes, as percentages of counterfactual baseline incomes, in SRES A1B, when using 2003, 2010, 2016 and 2016-edu SAMs




Notes: Figure shows the cumulative changes in incomes, expressed as percentages of counterfactual baseline incomes, for each American household income quintile, as a result of FUND's estimated climate change impacts on agricultural output, energy expenditure, expenditure building coastal defences and expenditure on reconstruction after storm damages. The case study was run from 2020 to 2100, using the four different US SAMs constructed in Chapter 4, for 2003, 2010, 2016, and 2016-edu, where 2016-edu was an alternatively disaggregated 2016 SAM, as described in Chapter 4. Q1 represents the income of the lowest income quintile, and Q5 represents the income of highest income quintile. The counterfactual baseline incomes assume no effects from climate change.

Comparing results generated using the two 2016 SAMs does not, however, provide support for the conjecture in Pieters (2010) that differing inequality effects from growth in different sectors cannot be observed unless SAMs have factor accounts disaggregated by industry, not just by level of labour education and capital, as the different sectors produced markedly different impacts on inequality ratios when using both SAMs.

Figure 8.9 - Largest percentage change in each inequality ratio that was observed in any scenario at any point during the 2020 to 2100 time period, for each sector, and when using each of the four US SAMs to generate results




Notes: Figure shows, when using each of the four US SAMs, 2003, 2010, 2016 and 2016-edu, the largest percentage changes in the four American inequality ratios, Q5/Q1, Q5/Q3, Q3/Q1, (Q4+Q5)/(Q1+Q2), that were observed in any of the four scenarios, SRES A1B, A2, B1 and B2, at any point during the 2020 to 2100 time period. Q1 represents the income of the lowest income quintile, while Q5 represents the income of the highest income quintile. The percentage changes were driven by impacts to four economic sectors, agriculture, energy, coastal defence from sea-level rise (SLR), and repairs after tropical and extratropical storms. These impacts were estimated using the FUND model, as described in Chapter 6. Changes driven by impacts to each of the four FUND sectors are shown separately, where blue, red, green and purple bars respectively represent maximum changes driven by climate change impacts on agricultural output, energy demand, coastal defence expenditure, and repairing economic damages from tropical and extratropical storms. Positive (negative) changes indicate increases (decreases) in the relevant inequality ratio.

## 8.3 Summary

This chapter analysed the results from the case studies in Chapters 6 and 7 for insights on the research questions outlined in Chapter 2.

While the FUND case study indicated that agriculture and energy expenditure, particularly agriculture, are likely to be the sectors responsible for the largest inequality effects, an analysis of unit changes to each sector suggested that SLR and storms impacts also have the potential to generate large effects, if the FUND model is incorrect in estimating that impacts from these sectors will be far smaller than those for other sectors. Similarly, unit changes to water output typically produced large effects, so this sector, which had to be excluded from the FUND case study, could also be a significant driver of inequality.

The Alaskan case study found that changes to infrastructure, fisheries and especially oil are most likely to drive changes in inequality. Modelling unit changes to the different sectors, however, implied that fisheries and tourism could play larger roles than the Alaska case study suggested, as the magnitudes of impacts from tourism in this analysis were closer to those from other sectors than was observed in the case study, and fisheries were even found to have the largest impact on two of the ratios.

With regards to whether changes to sectors had a consistent effect on inequality across countries, a unit increase in expenditure on coastal defence, which decreased inequality, was the only sector where this was the case. Unit increases in all other sectors produced effects that varied by country.

In addition, in some countries, increased energy expenditures started off negative but then became positive as time went on. Similarly, while FUND estimated positive agricultural impacts throughout the time period used for the FUND case study, had the model been run for longer, the benefits of $CO_2$ fertilisation would have been cancelled out by growing negative impacts from climate change level effects. Energy and agriculture, thus, could produce different inequality effects in a country at different points in time.

While the Alaska case study and the Mexican and Zambian results from the FUND case study demonstrated that the poor could do least well out of climate change, the results from Ethiopia and India in the FUND case study conversely showed that it is also plausible that the poor could benefit most from a warmer world. Meanwhile in Egypt, a clear pattern was not discernible. The results from this thesis, thus, do not support a simple narrative, such as ‘climate change will always hit the poor the hardest’.

Meanwhile, no moderate or strong correlation could be found between 2017 GDP per capita, in USD, in the seven countries, and the changes in inequality ratios arising from unit exogenous increases in the different sectors. In contrast, the correlations between the effects on inequality ratios of unit exogenous increases of each given sector, and starting levels of inequality were frequently high.

These results suggest that more unequal countries could generally experience greater changes in inequality ratios than their more equal counterparts. The results from the FUND case study, however, demonstrated that correlations between impacts from unit exogenous increases in the different sectors, and starting levels of inequality, played only a very small role. The correlations, or lack thereof, between the scale of exogenous impacts and starting levels of inequality were far more influential.

In the FUND case study, there typically weren't correlations between exogenous changes to sectors and starting levels of average income and inequality, so, with the exception of expenditure on repairing storm damages, no convincing correlation was found between the maximum changes in inequality ratios in the FUND case study and starting income and inequality. Changes in inequality from increased expenditure on repairing storm damages generally, but not always, displayed strong positive correlations.

The largest cumulative impact[132] observed in the FUND case study, as a percentage of most recent YoY income growth, was only 294%. While costs of over 14 times the most recent year's exogenous YoY growth were generated for Alaska from infrastructure, these cumulative effects occurred in 2099. As one is comparing *cumulative* impacts with YoY growth, such loses would be more than compensated for by many previous decades of growth. The results of this thesis thus do not support the suggestion in Dennig et al. (2015) and Rozenberg and Hallegatte (2015) that climate change may disrupt the notion that 'growth is good for the poor'.

The cumulative changes in inequality ratios in the FUND case study appear small, as no ratio changed from its baseline by more than 2.33%. Moreover, in all countries except Vietnam, which saw the largest proportional impacts, the maximum magnitudes of changes in inequality ratios did not exceed 6% of the historical standard deviations. Thus, even over eighty-years, let alone a shorter time-scale, FUND-estimated impacts on income inequality, for nearly all countries, typically looked fairly small compared to recent changes in inequality that were unrelated to climate change.

[132] All FUND-estimated total impacts were positive across all countries and scenarios, primarily due to sizable projected agricultural benefits from carbon dioxide ($CO_2$) fertilisation and the level of climate change. It was, however, still interesting to explore the scale of the estimates, by comparing the magnitudes of the impacts generated by FUND with YoY growth.

For Vietnam, the maximum cumulative change in inequality ratio was equivalent to approximately two fifth of the standard deviation of inequality ratios since 1992. This sounds reasonably large; however, inequality ratios in Vietnam have historically been low variance. So even the Vietnamese results did not correspond to a sizable change in inequality.

Changes to inequality ratios in the Alaska case study were often larger, and indicated that the H/L ratio could potentially increase by 16.55%. This sounds sizable; however, this could not be verified, as historical standard deviations of inequality ratios for the appropriate household groupings were not available.

Meanwhile, by comparing results generated using the 2016 US SAM, which was used in the FUND case study, to those generated using the US 2003 SAM, 2010 SAM and 2016 edu-SAM, this chapter also explored the sensitivity of results to uncertainty surrounding economic structures.

While many key features of results were preserved when using the US 2013, 2010 and 2016 SAMs, including which sectors were primarily responsible for inequality impacts, and similar ranges and progressions of absolute and percentage impacts, albeit with some notable differences at any given instance in time, the sensitivity analysis demonstrated that changes to US economic structure over even this short period of time could reverse the relationship that agriculture and, in particular, energy had on some measures of inequality. As agriculture and energy were the two sectors most responsible for inequality impacts, these changes were important.

While differences between results generated using the two 2016 US SAMs did exist, for example, whether proportional impacts were greater for the third or fourth income quintiles, such differences were small in comparison to those observed when using American SAMs from different time periods. Nevertheless, they were sufficient to reverse the relationship between the energy sector and two inequality ratios. Thus, while industry-by-industry disaggregated factor accounts were not necessary to observed differing inequality effects from growth in different sectors, the aggregated nature of labour accounts distinguished solely by educational level lost sufficient information to produce different inequality results for a key sector

# Chapter 9 – Conclusion

This chapter reviews the thesis' conclusions and contributions, demonstrates how the thesis has met its stated goals, and reflects on the limitations of the project. Section 9.1 summarises the thesis' motivation, goals and conclusions. Section 9.2 explores the thesis' limitations, while Section 9.3 reflects on other contributions made and implications for future research.

## 9.1 Thesis motivation, goals and conclusions

Coupled economic-environmental models have typically been used to estimate impacts of climate change on gross domestic product (GDP) or production of a specific commodity. Where inequality was considered, studies generally focused on exploring how impacts may differ across regions or time. Intra-regional inequality, particularly within-country inequality, is generally not studied, and, where it has been, hypothetical income and impacts distributions were frequently used. Many studies from other disciplines, however, suggest that climate change is unlikely to equally impact different income groups.

While the relationship between inequality and growth is currently unclear, they could plausibly interact. Beyond purely economic dynamics, inequality could also cause political instability, regulatory capture, increased crime, and moral concerns. Behavioural studies moreover indicate that relative income is a key factor in wellbeing. Finally, if climate change were to cause the poor's incomes to fall while average incomes still rise, this could sever the link between GDP growth and poverty reduction. So, ending poverty, reducing inequality, and taking action against climate change, three of the United Nation's Sustainable Development Goals (SDGs), could be interlinked tasks.

This thesis did not attempt to comprehensively answer all questions surrounding climate change and within-country income inequality, or even to definitively answer the six research questions that formed the focus of this thesis. Its goal was to probe an area that had hitherto been neglected, to better understand why this area had not been properly addressed to date, to put forward a methodology to facilitate studies into within-country income inequality and climate change, and to generate results for a range of scenarios, so beginning exploration into this highly complex and uncertain problem.

A methodology was proposed that extends coupled economic-environmental models so that, in addition to estimating impacts on GDP or production, they can also estimate impacts on within-country income inequality. The methodology was piloted for two case studies, one for each of the two identified types of coupled economic-environmental models, that is, impact studies and

Integrated Assessment Models (IAMs). These two case studies illustrated how the proposed methodology is applied, and were also used to address six research questions. These questions were chosen to explore key areas of interest identified in the literature review. Firstly, the hypothesis that inequality effects from climate change may vary depending on which sector is driving the changes, and that the relationship between growth in a sector and inequality may vary across countries. Secondly, if certain household groups appear particularly vulnerable to climate change. Thirdly, if wealthier or more equal countries are less vulnerable to climate change inequality effects, and finally, if the induced changes to inequality are relatively large or small.

To review the conclusions drawn from the case studies, let us revisit each research question in turn.

### 9.1.1 Climate change induced changes to which sectors seem likely to have the greatest effect on within-country income inequality?

The Climate Framework for Uncertainty, Negotiation and Distribution (FUND) case study indicated that impacts to agriculture and energy, particularly the former, are likely to have the largest impact on inequality. This was heavily influenced, however, by FUND predicting that these sectors experienced the largest exogenous changes, as the unit change analysis indicated that impacts on coastal defence and storm repair expenditures frequently produced similarly sized or even larger effects. Similarly, in the Alaska case study, impacts on infrastructure spending, fisheries and especially oil were responsible for the largest changes in inequality. The unit change analysis, however, indicated that impacts on fisheries and tourism could play a more important role that the case study indicated. Thus, once again, relative sizes of exogenous changes across sectors, as estimated by the impact studies, were primarily responsible for which sectors predominantly drove changes in inequality.

### 9.1.2 Do impacts to certain sectors consistently increase within-country income inequality across different economies? Or do impacts in some countries reduce inequality and in other countries increase inequality?

Changed expenditure on coastal defence was the only sector that had a consistent effect on inequality ratios across all countries, which was to decrease inequality. Unit increases in all other sectors increased inequality ratios in some countries yet decreased them in others. Generally, a unit increase in a sector changed all inequality ratios in a country in the same direction. In addition, as agricultural and energy sectors could potentially initially benefit from global warming, before impacts turn negative at higher temperature levels, effects on inequality from changes to these sectors could act in opposite directions at different points in time.

### 9.1.3 Do certain household groups seem particularly vulnerable across economies?

This thesis did not find evidence to support a simple narrative, such as 'climate change will always hit the poor the hardest'. While results for some countries demonstrated that the poor could do least well out of climate change, results for others suggested the converse. Moreover, cases were found where the skew of proportional impacts across household groups varied with time and, in one instance, no general pattern was discernible.

### 9.1.4 Is there evidence to support the conclusion in Rozenberg and Hallegatte (2015) that starting levels of average income and within-country income inequality may affect the extent that climate change impacts on inequality?

Results indicated that the frequently high and always low correlations between impacts from unit exogenous increases in the different sectors and, respectively, starting inequality and average income, played only very small roles in determining whether more wealthy or unequal countries experienced greater changes in inequality from climate change. The correlations, or lack thereof, between the scale of exogenous impacts and starting levels of inequality and average income were far more influential. In the FUND case study, these latter correlations were typically weak, so, with the exception of exogenous changes in expenditure on repairing storm damages, no convincing correlations were found between the maximum changes in inequality ratios and starting inequality or average income. Changes in inequality from increased expenditure on repairing storm damages generally, but not always, displayed strong positive correlations with starting inequality and average income.

### 9.1.5 Are within-country income inequality effects relatively small in many or all scenarios compared to projected growth in average incomes? Alternatively, is it possible, as suggested by Dennig et al. (2015) and Rozenberg and Hallegatte (2015), that increased inequality from climate change might cancel out improvements in overall standards of living from GDP growth for low-income households?

The largest cumulative impacts[133] observed in the FUND and Alaskan case studies amounted, respectively, to approximately 3 and 14 years of exogenous year-on-year (YoY) growth. As one is comparing *cumulative* impacts with YoY growth, this suggests that the cumulative impacts of climate

[133] All FUND-estimated total impacts were positive across all countries and scenarios, primarily due to sizable projected agricultural benefits from carbon dioxide ($CO_2$) fertilisation and the level of climate change. It was, however, still interesting to explore the scale of the estimates, by comparing the magnitudes of the impacts generated by FUND with YoY growth.

change on household incomes are unlikely to significantly diminish the benefits of cumulative exogenous growth in incomes.

### 9.1.6 Is it only in the most extreme climate damage scenarios and time frames that relatively sizable within-country income inequality effects emerge? Or are they plausible in shorter-term, moderate scenarios?

The cumulative changes in inequality ratios appeared small in the FUND case study, as no ratio changed from its baseline by more than 2.33%. Moreover, in all countries except Vietnam, which saw the largest proportional impacts, the maximum magnitudes of changes in inequality ratios did not exceed 6% of the historical standard deviations. Thus, even over eighty-years, let alone a shorter time-scale, FUND-estimated impacts on income inequality, for nearly all countries, typically looked fairly small compared to recent changes in inequality that were unrelated to climate change.

For Vietnam, the maximum cumulative change in inequality ratio was equivalent to approximately two fifths of the standard deviation of the relevant inequality ratio since 1992. This sounds reasonably large; however, inequality ratios in Vietnam have historically been low variance. Thus, even the Vietnamese results did not correspond to a sizable change in inequality.

Changes to inequality ratios in the Alaska case study were often much larger, and indicated that one ratio could potentially increase by 16.55%. This sounds sizable; however, this could not be verified, as historical standard deviations of inequality ratios for the appropriate household groupings were not available.

## 9.2 Thesis limitations

There are many limitations to this thesis. Firstly, FUND assumes that economic growth from one year to the next was exogenous, i.e. not affected by climate change, and this assumption was also made in the Alaska case study. In reality, it is likely that capital could be damaged by climate change impacts, or that investment suffers due to increased resources being directed towards repairs. Dell et al. (2012), for example, did a panel regression on historical data, and found that, in lower-income countries, a 1$^{o}$C increase in temperature reduced the annual growth rate, on average, by 1.3 percentage points. Thus, exogenous rather than endogenous growth may be the biggest limitation of this thesis as, like with compound interest, small changes in the short-run can have large impacts in the long-run.

It is plausible the endogenous growth could significantly alter results and so, in turn, conclusions. Specifically, it could increase climate change induced income inequality, and reduce YoY growth rates, so increasing annual impacts as a percentage of YoY growth. The latter could prompt a re-evaluation of whether climate change could cancel out improvements in standards of living for some or all household groups, for example, by severing the relationship between rising average incomes and increased incomes for the poor. In addition, if, say, poorer or more unequal countries appear to experience greater impacts to growth rates than their wealthier or more equal counterparts, then this could change whether starting levels of average income and within-country income inequality affect the extent that climate change impacts on inequality. Exploring how climate change may alter rates of growth is, thus, a crucial next step to better understand the impact of climate change on economic inequality, or, for that matter, GDP.

Results are, of course, only as good as the assumptions that underpin them. In addition to the general criticisms levied at IAMs, which were detailed in Chapter 3, it is important to emphasise that there are issues specifically surrounding FUND. Firstly, as mentioned earlier, total impacts in the FUND case study were positive in all countries and scenarios throughout the time period, primarily down to sizable projected agricultural benefits from carbon dioxide ($CO_2$) fertilisation and the level of climate change; although agricultural benefits diminish but don't turn negative by the end of the time period.

As highlighted in Chapter 6, there are concerns around FUND's estimated impacts of $CO_2$ fertilisation on agricultural yields, as the impact function relies on studies published between 1992 and 1996. More recent studies on this topic typically estimate more moderate benefits from $CO_2$ fertilisation. This is because early experiments took place in enclosed greenhouses, rather than in the open air using technological innovations, such as free-air concentration enrichment (FACE) technology (Long et al., 2006). Long et al. (2006), for example, suggests that benefits from $CO_2$ enrichment could be 50% lower than earlier estimates.

Other studies raise doubts about FUND's level of climate change agricultural impact function. Schlenker and Roberts (2009), for example, indicates that once the optimal temperature has been past, benefits should fall away and turn to costs at a much faster rate than the quadratic function specified in FUND. Schlenker and Roberts (2009) also casts doubt on the degree of agricultural adaptation to climate change assumed in FUND. Finally, FUND's conclusion that climate impacts on agriculture were positive throughout the period for all countries in the study, despite the optimal regional temperature above preindustrial times being exceeded in all regions and scenarios by 2100, is contrary to observations that climate change is already having a negative impact on global agricultural production (Lobell et al., 2011).

As seen in Chapter 8, agricultural impacts were typically larger than those from other sectors, so the agricultural impact functions had a strong influence on overall results. With more moderate benefits from $CO_2$ fertilisation, level-related costs emerging rapidly after the optimal temperature is exceeded, and less optimistic adaptation assumptions, FUND could project agricultural costs rather than benefits, and total impacts netted across all sectors could turn negative.

One should, however, note that Chapter 6's comparison of the sizes of FUND's estimated reduced water utilities outputs to baseline water utilities outputs, suggested that FUND's estimates for this sector were too large. This was why water was excluded from the FUND case study. Thus, in this regard, FUND's estimates may be overly pessimistic.

Nevertheless, FUND is, in general, more optimistic about the economic impacts of climate change than other prominent IAMs, such as the Dynamic Integrated Climate-Economy (DICE) model. For example, FUND doesn't model climate 'tipping points', such as the Greenland ice sheet melting, where a threshold is breached that leads to catastrophic climate change. In contrast, such impacts are responsible for around 25% of the estimated social cost of carbon (SCC) in Policy Analysis of the Greenhouse Effect (PAGE) (Hope, 2013). In a clear indication of FUND's overall optimism, FUND produces much lower SCC estimates, for a given discount rate, than the other two IAMs. For example, as seen in Table 3.1 in Chapter 3, assuming a 5% discount rate, the SCCs estimated by PAGE, DICE and FUND are respectively 23, 12 and 3 USD per tonne of carbon. The positive total impacts estimated in the FUND case study are, thus, controversial, and many researchers would argue that net effects would be negative by 2100, and possibly already are so.

Many researchers would also query the optimism in the Alaskan impact studies. As discussed in Chapter 7, there is great uncertainty around how climate change may affect certain Alaskan sectors. For example, many undiscovered oil reserves could lie under the arctic ocean and become accessible due to melting sea ice. On the other hand, extraction costs are anticipated to be high due to difficult weather, including possibly more intense Arctic cyclones, the inherent challenges of offshore extraction, and the remoteness of sites, with their accompanying lack of existing infrastructure. As such, it is unclear whether exploiting such assets will be financially viable. Similarly, as a result of reduced sea-ice, Arctic oceans may absorb more $CO_2$, and thus become more acidic, which could undermine calcifying species, such as pteropods, mussels, and clams. Changing ocean temperatures could also lead to fish migrating from lower latitudes to higher latitudes, with invasive species possibly disrupting existing species. On the other hand, warmer Arctic oceans and reduced sea ice might boost primary production through photosynthesising phytoplankton, which, in turn, could increase Arctic fish stocks. Thus, while the studies used in the Alaska case study explored scenarios where the fisheries and oil sectors enjoyed large benefits, one should remember that such assumptions are controversial and could be overly optimistic.

Exogenous changes to sectors in both case studies could, thus, plausibly differ from those modelled, and, quite possibly, be more negative. The analysis in Section 8.1.1 of Chapter 8 is particularly useful in this light, as it explored, for all seven countries plus Alaska, the effects on inequality ratios of a unit exogenous increase in each sector. The effects from these unit changes are independent of any models or studies subsequently used to estimate by how many units a sector is exogenously changed. As such, if one had greater confidence in exogenous changes estimated by another IAM or set of impact studies, the results from the unit change analysis could be used, in combination with the exogenous changes estimated by the alternative models, to quickly generate revised inequality impacts.

Data availability also introduced limitations. Firstly, this thesis was unable to explore exogenous changes to all sectors that could be impacted by climate change. For example, FUND's forestry impact estimates could not be included in the analysis, as FUND's output for this sector estimated changes to producer and consumer surpluses, which could not be used as an input in input-output analysis (IOA). As another example, an economic impact study could not be found for Alaskan agriculture. Agriculture is currently a relatively small part of the Alaskan economy, but it could grow in importance as Alaska warms. Thus, while impacts to the main sectors likely to be affected by climate change were explored, this thesis does not claim to have comprehensively studied the impacts of climate change on income inequalities. It is instead an early attempt at the subject. Moreover, when impact studies for other sectors become available, the methodology outlined in Chapter 5 could be used to explore the impacts of these exogenous changes.

Data also restricted the number of countries that could be studied. In particular, relatively few high and upper-middle income countries were included, and the countries included had Gini coefficients that spanned only 63% of the range of all countries' Gini coefficients. Exploring impacts on additional countries, particularly wealthier countries and those at the two extremes of the inequality spectrum, would help further illuminate if starting levels of average income and within-country income inequality may affect the extent that climate change impacts on inequality. Similarly, only six of FUND's 16 regions featured in the FUND case study. As discussed in Chapter 6, some regions were estimated to experience far larger relative exogenous impacts to sectors than in other regions. It would therefore be useful to include countries from other FUND regions, for example, a European region.

The final key data limitation was that a time series of historical income inequality ratios could not be found for the household income groups used in the Alaska case study. This meant that the Alaskan results could not be analysed in the discussion exploring whether the inequality impacts generated by climate change were comparable in magnitude to fluctuations in inequality in recent memory. This was disappointing, as the Alaskan case study indicated than an inequality ratio could increase by 16.55%, so it is plausible that this large proportional impact could have been comparable in magnitude to, or even possibly exceeded, historical fluctuations.

IOA's key assumption, that technical coefficients are constant, was another limitation, as this was a crude approximation that did not allow economies to adapt to mitigate the effects of exogenous changes. The empirical stability analysis in Chapter 5, however, demonstrated that it is workable in practice, if not in theory, over the short to medium-term, and thus can be used to generate plausible scenarios of economic responses to climate change impacts in a given year.

The empirical stability analysis in Chapter 5 also showed that social accounting matrices (SAMs) change significantly over the medium to long-term. Moreover, the sensitivity analysis in Chapter 8 found that while many key features of results were preserved when using the US 2013, 2010 and 2016 SAMs, including which sectors were primarily responsible for inequality impacts, and similar ranges and progressions of absolute and percentage impacts, changes to US economic structure over even this short period of time could reverse the relationship that agriculture and, in particular, energy had on some measures of inequality. As agriculture and energy were the two sectors most responsible for inequality impacts, these changes were not immaterial. In short, economies in, say, 2100, are unlikely to share many characteristics with the SAMs used in the FUND case study. While this was undoubtably a shortcoming, it was mitigated by taking a scenario approach to uncertainty. All results were interpreted as plausible scenarios, not predictions. Moreover, results were not viewed as vulnerability analyses for specific countries. They were instead considered collectively to see if general patterns emerged and to explore the range of results.

The sensitivity analysis in Chapter 8 also revealed that using the American 2016-edu SAM, instead of the 2016 SAM, reversed the relationship between the energy sector and two inequality ratios. Thus, while industry-by-industry disaggregated factor accounts were not necessary to observe differing inequality effects from growth in different sectors, the aggregated nature of labour accounts distinguished solely by educational level lost sufficient information to produce different inequality results for a key sector. The US SAM, which was built from scratch, and the Alaska SAM, which had its labour accounts disaggregated in this thesis, were the only SAMs used in the case studies with labour accounts disaggregated by industry. Labour accounts in the other SAMs were disaggregated, for example, by educational level, ethnicity, rural or urban location, or region. It is thus possible that results generated using non-US SAMs could suffer from aggregation bias, a common problem in IOA. Consequently, it would be useful to repeat the analysis performed in this thesis using SAMs with alternatively disaggregated labour accounts.

Beyond aggregation bias and assuming fixed technical coefficients, further limitations stem from the use of IOA. Firstly, as explained in Chapter 3, IOA is a demand-driven model, so supply-side effects were overlooked in this thesis. Similarly, effects on wealth could not be modelled, as IOA models flows not stocks. Meanwhile, modelling changes in energy *consumption* would have required changing business activities' and household's technical coefficients. The latter is not possible in IOA, so changes in energy expenditure were instead modelled as changes in *investment* in electricity. A consequence of this was that other budget constraints[134], that is, financing increased expenditure on construction or energy through changes in borrowing or savings, could not be modelled, as this would have required an endogenous capital-savings account. This was not possible, as IOA needed this account to be a component of final demand, so that impacts of changes in energy investment could be estimated.

The SAMs used also had limitations, including that one cannot explore inequality within household groups, or model skewed impacts within economic sectors, for example, the distribution of a national reduction in agricultural yields being borne predominantly by poorer farmers. In addition, non-market activities, such as subsistence farming, were not included in the SAMs[135], and SAMs were based on survey data, which always have shortcomings, such as poor participation at the very upper and lower ends of the income distribution.

All these limitations emphasise that this thesis has not definitively answered all questions surrounding climate change and inequality, or even the research questions that formed the focus of this thesis. It has begun exploration into this complex subject, but clearly there is further work to be done.

## 9.3 Other contributions and implications for further research

Inequality effects appear to be small, as *cumulative* impacts never amounted to more than 14 times the most recent YoY growth, and frequently were equivalent to less than one year of YoY growth. In addition, the maximum change to an inequality ratio observed in the FUND case study was

[134] Only one type of budget constraint was explored in this thesis for increases in expenditure on construction and energy. Specifically, expenditures on other goods and services were changed, in proportion to existing spending on those goods and services, so that total expenditure remained constant.

[135] Attempts are sometimes made to value non-market activities to include them in SAMs, but this did not occur in the SAMs used in this thesis.

approximately two fifths of the given ratio's low historical standard deviation. From these findings, one might conclude that the impacts from climate change on income inequality were too small to merit increased model complexity and researchers' time, and that future studies should concentrate on exploring other aspects of the economic consequences of climate change. There are, however, three crucial caveats to this conclusion.

Firstly, historical ratio data was not available for Alaska, so one could not compare the ratio changes in this case study with historical variation. This was a significant shortcoming, as the Alaskan case study indicated a maximum ratio change that was over seven times larger than the maximum ratio change observed in the FUND case study.

Secondly, FUND's estimated exogenous sector changes could be substantially smaller than those indicated by other studies, as FUND is generally relatively optimistic about the impacts of climate change. For example, its estimated SCC is over seven times lower than PAGE's estimate.

Finally, YoY growth rates in both case studies were exogenous and so not impacted by climate change. Studies indicate that, in reality, this is unlikely to be the case. Moreover, small changes in YoY growth rates could have a large impact over time. Endogenous growth thus has the potential to increase the magnitude of cumulative climate change impacts and decrease the YoY growth rate, so impacting on both inequality ratio changes and cumulative impacts on households as percentages of YoY growth.

As explored in Chapter 2, the implications of sizable changes in inequality could be widespread, including via potentially affecting growth, political stability, corruption, crime, or even severing the link between rising average income and poverty reduction. High levels of inequality could also pose moral concerns. As such, and in light of the three caveats listed above, this thesis does not suggest that researchers should not further study the impact of climate change on inequality. The analysis does, however, reveal that a key bottleneck, exogenous growth, must be addressed to enable further progress. Helpfully, endogenous economic growth has received research focus in recent years; such as in Burke et al. (2015) and Dell et al. (2012). Attempts at incorporating endogenous growth into IAMs have, however, generally not been empirically founded; for example, Fankhauser and Tol, (2005). Thus, if results from studies such as Burke et al. (2015) were to be integrated into IAMs, this would be an important addition to the field that would enable a fuller exploration of the impacts of climate change on inequality, and indeed GDP.

In addition, it is advisable that IAM impact functions are urgently updated to reflect the most up-to-date knowledge. As discussed in Chapter 3, all IAMs, not just FUND, are criticised for having impact functions based on studies conducted sometimes decades ago. As highlighted in Chapter 8, such studies are often more optimistic than more recent research.

This thesis has identified many challenges in studying the impact of climate change on income inequality, including uncertainty around future economic structures and having to introduce some crude assumptions, such as, fixed technical coefficients. This thesis, nevertheless, has also demonstrated that such challenges can be managed by taking a scenario approach to uncertainty, and understanding that results should not be interpreted as predictions for any given country, but rather that results from many countries should be considered collectively to identify any general patterns and explore the range of effects.

In addition to suggesting that the impact of climate change on income inequality is a fruitful topic for further research, a further contribution from this thesis is the coupling methodology. This could be used in combination with other coupled economic-environmental models, including ones that do not study the economic impacts of climate change, to explore inequality effects from a wide range of environmental economic problems. Furthermore, when further research has been done into the impact of climate change on growth, the case studies from this thesis could be rerun using endogenous growth rates. The methodology could once again be deployed when SAMs for other countries or impact studies for other sectors become available.

As suggested in Chapter 8, the inequality impacts from a unit exogenous change in each sector could be used in combination with any study estimating exogenous changes for those sectors, to quickly generate inequality impacts. This is because IOA is a linear model, and the effects from these unit changes are independent of studies estimating by how many units a sector is exogenously changed. The results from the unit change analysis are particularly useful, in this light, given that the impact studies used in the two case studies were generally relatively optimistic in comparison to the rest of the literature. The unit change analysis results could easily be used with estimates from more pessimistic studies.

The breakdown of impacts into direct and indirect effects was an additional contribution. It illustrated the importance of taking a macroeconomic approach and considering how sectors impact on one another, rather than modelling each sector individually and then summing the results, as was done in Rozenberg and Hallegatte (2015) or indeed FUND itself. As one can see in Appendix H, while some impacts were nearly entirely composed of direct effects, for others, indirect effects were far greater. Thus, in many cases, taking a microeconomic approach and then summing the results, as is frequently done in the literature, would produce a very incomplete picture.

As discussed in Chapter 2, the few papers that incorporated within-region inequality into IAM estimates of the SCC used hypothetical damage incidences across income groups. Revised estimates of the SCC were not calculated in this project, as conclusions with quantified uncertainties were deemed inappropriate given the deep uncertainties present. However, for those researchers who wish to focus on the SCC, this thesis can provide a more informed alternative to hypothetical skews of impacts across household groups.

The US SAM time-series and the adapted Alaskan SAM can also be used by other researchers. The time-series is particularly useful, given that so few SAM time-series currently exist. Furthermore, the stability analysis in Chapter 5, that empirically tested IOA assumptions and predictions, and explored the extent that key economic characteristics were preserved across time, is valuable because previous work in this area used input-output table time-series, which map only a small subset of an economy.

This thesis also provides evidence refuting the conjecture in Pieters (2010) that industry-by-industry disaggregated factor accounts are necessary to observe differing inequality effects from growth in different sectors. However, the aggregated nature of labour accounts distinguished solely by educational level did lose sufficient information to produce different inequality results for a key sector. This thesis has thus identified a key source of aggregation bias that is highly relevant for IOA, as most SAMs with disaggregated labour accounts are typically disaggregated at a high level, such as by education, rather than by industry.

Finally, the Alaskan case study was the first macroeconomic study of the impacts of climate change on an arctic region. As discussed in Chapters 3 and 7, the Arctic is of particular interest in the climate change literature, as changes are expected to be greater towards the poles than elsewhere in the world.

## 9.4 Summary

This thesis aimed to probe the impact of climate change on within-country income inequality, an area that had hitherto been neglected, to better understand why this area had not been properly addressed to date, to put forward a methodology to facilitate studies into within-country income inequality and climate change, and to generate results for a range of scenarios, so beginning exploration into this highly complex and uncertain problem.

Chapter 2 presented a history of economists' evolving attitudes towards income inequality as an economic question, which was used to help understand why this research area is frequently overlooked. Chapter 5 put forward a coupling methodology that enables effects on income inequality to be modelled by coupled economic-environmental models. Meanwhile, Chapters 6 and 7 piloted the coupling methodology to generate results for a range of scenarios in two case studies. These scenarios were then analysed in Chapter 8 to explore key areas of interest that were identified in the literature review. The thesis has thus met its goals.

There are, of course, limitations to the work. Firstly, YoY growth was exogenous, that is, not impacted by climate change. Secondly, the IAM and impact studies used to estimate exogenous changes to sectors in the case studies were at the optimistic end of the relevant literature. Data availability also introduced limitations, for example, on the number of sectors and number of countries that could be included in the study, especially wealthier countries and those at the extremes of the inequality spectrum. Using IOA meant assuming constant technical coefficients, which are a crude approximation; although, empirical analysis indicated that the assumption works in the short or medium-term in practice, albeit not in theory. IOA also resulted in the methodology being demand-side only; supply-side effects could not be studied. Similarly, impacts of climate change on wealth could not be considered, and using IOA placed limitations on the budget constraints that could be modelled. Finally, the SAMs themselves restricted the thesis, by not enabling exploration of within household group inequality, skewed impacts within an economic sector, or impacts on subsistence farming. They may also suffer from aggregation bias, as labour accounts were often not disaggregated by industry. Many of these shortcomings, however, reflect that this thesis has not definitively answered all questions surrounding climate change and inequality, or even the research questions that formed the focus of this thesis. It has begun exploration into this complex subject, but clearly there is further work to be done.

Unsurprisingly, this thesis revealed a complex picture that did not support any simple narrative, such as “climate change is likely to hurt the poor the most”. While scenarios emerged where this was indeed the result, others could be found where the opposite was true, and many presented a more mixed picture. Similarly, while agriculture and energy, for example, were typically found to generate the largest inequality impacts in the FUND case study, there were exceptions, and only effects due to increased spending on coastal defence impacted on inequality in all countries in the same way. When examining unit changes to different sectors, those that had produced relatively small impacts in the case studies demonstrated the potential to generate sizable inequality impacts if the estimated exogenous changes applied were notably underestimated. Finally, for only one sector, expenditure on repairing storm damages, could any evidence be found to support the conjecture that there may be a correlation between starting inequality or average income and vulnerability to climate change induced income inequality.

Inequality effects appeared to be small, as *cumulative* impacts never amounted to more than 14 times the most recent YoY growth, and frequently were equivalent to less than one year of YoY growth. In addition, the maximum change to an inequality ratio observed in the FUND case study was approximately two fifths of the given ratio's low historical standard deviation. However, historical ratio data was not available for Alaska, so one could not compare the much larger ratio changes in this case study with historical variation. The IAM and impact studies used in the case studies were also generally more optimistic about the impacts of climate change than a lot of the literature, and YoY growth rates in both case studies were exogenous, which is likely unrealistic. As such, this thesis does not advise that researchers should not further study the impact of climate change on inequality. However, incorporating endogenous growth and more up-to-date impact studies should be top research priorities when exploring the effects of climate change on inequality or, indeed, GDP.

# Appendix A – Key characteristics of Special Report on Emissions Scenarios (SRES) families

| | **A1** | **A2** | **B1** | **B2** |
|---|---|---|---|---|
| **Economic growth** | Very rapid. Approximately a twenty-five-fold increase in world GDP by 2100. | Relatively slow. Approximately a twelve-fold increase in world GDP by 2100. | Intermediate growth rate. Approximately a sixteen-fold increase in world GDP by 2100. Growth increasingly skewed towards services. | Similar to A2. |
| **Global population** | Peaks at 9 billion, then slowly declines in latter half of twenty-first century to 7 billion in 2100 | Continuously increases to reach 15 billion in 2100 | Peaks at 9 billion, then slowly declines in latter half of twenty-first century to 7 billion in 2100 | Continuously increases, but at a slower rate than in A2, to reach 10 billion in 2100. |
| **Globalisation** | Extensive economic and social interactions. Very reduced inter-regional per capita income inequality, with the ratio of per capita income between developed and developing | Self-reliant nations. Reduced inter-regional per capita income inequality, but less so than in the other families. The ratio of per capita income between developed and developing | Global cooperation on economic, social and environmental problems. Reduced inter-regional per capita income inequality, but slightly less so than in A1. | Local, rather than global, solutions sought to economic, social and environmental problems. Reduced inter-regional per capita income inequality, more so than in the A2, but less so than |

| | | | | |
|---|---|---|---|---|
| | countries falling from 16.1 to approximately 1.5 in 2100. | countries falls to approximately 4.2 in 2100. | | in A1 and B1. |
| **Cleaner, more efficient technologies** | Energy intensity falls by approximately 80 to 86 percent over course of century. Three fuel storyline subfamilies: approximately 31% of energy is zero-carbon by 2100 (A1F1); approximately 61% of energy is zero-carbon by 2100 (A1B); and approximately 85% of energy is zero-carbon by 2100 (A1T). | Energy intensity falls by approximately 65% over course of century. Approximately 28% of energy is zero-carbon by 2100. | Energy intensity falls by approximately 92% over course of century. Approximately 52% of energy is zero-carbon by 2100. | Energy intensity falls by approximately 76% over course of century. Approximately 49% of energy is zero-carbon by 2100. |

Notes: Table outlines the characteristics shared by each SRES family, A1, A2, B1 and B2, broken down by four key factors driving emissions: economic growth; population; globalisation; and adaptation of cleaner and more energy efficient technologies. Family A1 is further divided into three sub-families, A1F1, A1B and A1T, which reflect different percentages of zero-carbon energy in total energy usage. In A1F1, the world remains heavily dependent on fossil fuels, in A1T, energy is primarily zero-carbon, while in A1B, there is a balance between the two fuel types.

# Appendix B – Key differences between the five Shared Socioeconomic Pathways (SSP) narratives

| | SSP1 | SSP2 | SSP3 | SSP4 | SSP5 |
|---|---|---|---|---|---|
| **Population** | Low: peaking around 8 billion, then slowly declining to around 7 billion by 2100 | Medium: peaking around 9 billion, then slightly declining | High: increasing, reaching 12.6 billion in 2100 | Medium: peaking around 9 billion, then slightly declining | Low: peaking around 8 billion, then slowly declining to around 7 billion by 2100 |
| **Economic growth** | Focus shifts away from growth and towards more general wellbeing | Good growth in some countries, while poor in others | Slow | Good growth in some countries, while poor in others | Rapid |
| **Inequality** | Reduced both across and within countries | Persists or improves only slowly | Persists or worsens | Increased both across and within countries | Reduced |
| **Meeting development goals** | Increasing commitment to achieving development goals | Slow progress | Countries focus on their own regions at the expense of broader-based development goals | Gap widens between knowledge and capital-intensive countries and labour-intensive, low-tech countries | Development of human capital seen as path to sustainable development |

| | | | | | |
|---|---|---|---|---|---|
| **Global cooperation** | Management of global commons slowly improves | Global and national institutions work together but make slow progress | Focus on domestic or, at most, regional issues | Knowledge and capital-intensive countries are internationally connected, while labour-intensive, low-tech countries are more isolated. | Global markets are increasingly integrated |
| **Achieving environmental sustainability** | Gradual increasing focus | Some improvements but there is environmental degradation | Low priority | Focus on local issues around middle and high-income areas | Local problems, such as pollution, are successfully managed |
| **Resource and energy intensity of production** | Decreases | Decreases | Intensive | Investments in both carbon-intensive and low-carbon sources | Adaption of resource and energy intensive lifestyles around the world |

Notes: Table outlines the differences between the five SSP narratives, SSP1, SSP2, SSP3, SSP4, and SSP5, in terms of population, economic growth, inequality, meeting development goals, global cooperation, achieving environmental sustainability, and resource and energy intensity of production. Table is adapted from Riahi et al. (2017).

# Appendix C – Challenges to adaptation and mitigation in the five Shared Socioeconomic Pathways (SSPs)

| | High challenges to mitigation | Intermediate challenges to mitigation | Low challenges to mitigation |
|---|---|---|---|
| High challenges to adaptation | SSP3 | | SSP4 |
| Intermediate challenges to adaptation | | SSP2 | |
| Low challenges to adaptation | SSP5 | | SSP1 |

Notes: Table shows how the five SSPs, SSP1, SSP2, SSP3, SSP4, and SSP5, embody a range of low to high challenges to adaptation and mitigation. These challenges stem from the aggregate effect of the characteristics outlined in Table 1.2. Table is taken from Riahi et al. (2017)

# Appendix D – Data sources for United States macro and micro social accounting matrices' (SAMs) elements

Table B.1 – Data forming macro-SAM elements

| SAM code | Data source |
|---|---|
| C1 | Gross output, from Bureau of Economic Analysis' (BEA's) use table (BEA, 2018c) |
| C2 | Imports, from National Income and Product Accounts (NIPAs) (FED, 2018b) |
| I1 | Tcom – Hcur1 – Gcur1 – Inv - Sd – Cap1 – R1 |
| I2 | Gross domestic income, from NIPAs |
| F1 | Compensation of employees, from NIPAs (BEA, 2018g) |
| F2 | Tfac – F1 – F3 – F4 |
| F3 | Taxation on production and imports less subsidies, from NIPAs |
| F4 | Current payments to the rest of the world: income payments, from NIPAs |
| Hcur1 | Personal consumption expenditures, from NIPAs (BEA, 2018h) |
| Hcur2 | Interest payments from households to enterprises, estimated by the author as described in Chapter 4 |
| Hcur3 | Personal current taxes + contributions for government social insurance, domestic + personal current transfer payments: to government, all from NIPAs, + interest payments from households to government, estimated by the author as described in Chapter 4 |
| Hcur4 | Consumption of fixed capital: private: households and institutions + personal saving, both from NIPAs |
| Hcur5 | Current taxes and transfer payments to the rest of the world: from persons, from NIPAs |
| Ecur1 | Personal income receipts on assets: personal dividend income + personal current transfer receipts: other current transfer receipts, from business (net) + proprietors' income with inventory valuation and capital consumption adjustments + rental income of persons with capital consumption adjustment + consumption of fixed capital: private: households and institutions, all from NIPAs, + interest payments from enterprises to households, estimated by the author as described in Chapter 4 |
| Ecur2 | Federal government: tax receipts on corporate income + state and local government: tax receipts on corporate income + federal government current receipts: income receipts on assets: dividends + state and local government current receipts: income receipts on assets: dividends + business current transfer payments (net): payments to government (net) + current surplus of government enterprises + |

| | |
|---|---|
| | consumption of fixed capital: government, all from NIPAs, + interest payments from enterprises to government, estimated by the author as described in Chapter 4 |
| Ecur3 | Consumption of fixed capital: private: domestic business + corporate profits with inventory valuation adjustment (IVA) and capital consumption adjustment (CCAdj) – taxes on corporate income – net corporate dividend payments, all from NIPAs. |
| Ecur4 | Current taxes and transfer payments to the rest of the world from business (net), from NIPAs |
| Gcur1 | Government consumption expenditures, from NIPAs |
| Gcur2 | Personal current transfer receipts: government social benefits to persons, from NIPAs, + interest payments from government to households, estimated by the author as described in Chapter 4 |
| Gcur3 | Interest payments from government to enterprises, estimated by the author as described in Chapter 4 |
| Gcur4 | Net government saving + consumption of fixed capital: government, both from NIPAs |
| Gcur5 | Government current transfer payments: government social benefits: to the rest of the world + government current transfer payments: other current transfer payments to the rest of the world (net), both from NIPAs |
| Inv | Change in private inventories, from NIPAs |
| Sd | – gross domestic product (GDP); statistical discrepancy (calculated from components) (IMA), flow, from NIPAs |
| Cap1 | Gross domestic investment – change in private inventories, from NIPAs |
| Cap2 | Change in private inventories, from NIPAs |
| Cap3 | – gross domestic product (GDP); statistical discrepancy (calculated from components) (IMA), flow, from NIPAs |
| Cap4 | Capital account transactions (net): government + capital account transactions (net): private: domestic business + capital account transactions (net): private: households and institutions – rest of the world; net lending (+) or borrowing (-) (capital account), flow, all from NIPAs |
| R1 | Exports of goods and services, from NIPAs |
| R2 | Current receipts from the rest of the world: income receipts, from NIPAs |
| R3 | Current taxes, contributions for government social insurance, and transfer receipts from the rest of the world: to persons, from NIPAs |
| R4 | Current taxes, contributions for government social insurance, and transfer receipts from the rest of the world: to business, from NIPAs |
| R5 | Government current tax receipts: taxes from the rest of the world + contributions for government social insurance: rest-of-the-world contributions + government |

| | |
|---|---|
| | current transfer receipts: from the rest of the world, from NIPAs |
| Tcom | Gross output, from use table + imports of goods and services, from NIPAs |
| Tind | Gross output, from use table |
| Tfac | Gross national income + current payments to the rest of the world: income payments, both from NIPAs (BEA, 2018i) |
| Thcur | Personal income + consumption of fixed capital: private: households and institutions + contributions for government social insurance, domestic + current taxes, contributions for government social insurance, and transfer receipts from the rest of the world: to persons, all from NIPAs (BEA, 2018j) |
| Tecur | National income + consumption of fixed capital + current taxes, contributions for government social insurance, and transfer receipts from the rest of the world: to business – national income: compensation of employees – taxation on production and imports less subsidies, all from NIPAs, + interest payments from households and government to enterprises, estimated by the author as described in Chapter 4 |
| Tgcur | Government current receipts + consumption of fixed capital: government – gross domestic income: subsidies – government current expenditures: interest payments: to the rest of the world, all from NIPAs |
| Tinv | Change in private inventories, from NIPAs |
| Tsd | – gross domestic product (GDP); statistical discrepancy (calculated from components) (IMA), flow, from NIPAs |
| Tcap | Cap1 + Cap2 + Cap3 |
| Trow | Current receipts from the rest of the world, from NIPAs |
| Estimates of interest payments | Author's estimates using personal income receipts on assets: personal interest income, government current expenditures: interest payments: to the rest of the world, current payments to the rest of the world: income payments on assets: interest, uses of private enterprise income: income payments on assets: interest and miscellaneous payments, net interest and miscellaneous payments on assets, government current expenditures: interest payments, all from NIPAs, Tgcur, F3, Hcur3, Ecur2, R5, and Financial accounts of the United States (FED, 2018d). Estimation procedure is described in Chapter 4. |

Notes: Table lists data sources and relevant calculations for each element in the US macro-SAMs. For brevity, the SAM elements are referred to using codes. A diagram of how codes map to SAM elements can be found in Figure 4.3 in Chapter 4.

Table B.2 – Data sources used to estimate proportions for disaggregating macro-SAM elements for the micro-SAMs

| **SAM code for element being disaggregated** | **Data source** |
|---|---|
| C1 | Flows from commodities to industries in BEA's make table (BEA, 2018b) |
| C2 | Imports of goods and services by commodity from use table |
| I1 | Flows from industries to commodities from use table |
| I2 | Value added by industry from use table |
| F1 | Disaggregated across industries using compensation of employees by industry from use table. Then US Current Population Survey (CPS) (Census, 2018a) and household income quintile income limits from Census Bureau's historical income tables (Census, 2018b) were used to disaggregate each industry across household groups, as described in Chapter 4. Finally, RAS procedure used to reconcile totals for each household group with distribution of total wages and salaries per income quintile, as indicated by Consumer Expenditure Survey (CES). |
| F2 | Gross operating surplus by industry from use table (BEA, 2018c) |
| F3 | Taxes on production and imports less subsidies by industry from use table |
| F4 | Value added of majority-owned U.S. affiliates by industry of affiliate (BEA, 2018e) |
| Hcur1 | First disaggregated into personal consumption expenditures by commodity from use table (BEA, 2018c). To disaggregate each commodity across household groups, used CES by expenditure category and household income quintile (BLS, 2018b), in combination with the Bureau of Labor Statistics' (BLS') glossary to match SAM commodities to their equivalent CES expenditure categories (BLS, 2018c). Finally, RAS procedure used to reconcile consumption totals for each household group with CES distribution of total expenditure by household group. |

| | |
|---|---|
| Hcur2 | Family holdings of debt by household percentile of income: any debt, from Survey of Consumer Finances (SCF) (Fed, 2018) |
| Hcur3 | While personal taxes component could use personal taxes by household income quintile from CES, no data could be found on distribution of loans taken out from the government across households groups, so this element was disaggregated in the proportions that would balance the SAM. |
| Hcur4 | Personal saving component used income after taxes – expenditures in CES. Consumption of fixed capital component used 'housing: maintenance, repairs, insurance, other expenses' category in CES. |
| Hcur5 | Money sent outside of the US: how much in total dollars given, from 2008 CPS immigration/emigration supplement (Census, 2018a), and household income quintile income limits from Census Bureau's historical income tables, as described in Chapter 4. |
| Ecur1 | Personal dividend income, personal current transfer receipts from business, proprietors' income, rental income and interest receipts used sources of income and personal taxes: interest, dividends, rental income, other property income by household income quintile, from CES. Consumption of fixed capital component used 'housing: maintenance, repairs, insurance, other expenses' category in CES. |
| Gcur1 | Federal national defense: consumption expenditures by commodity + federal national nondefense: consumption expenditures by commodity + state and local: consumption expenditures by commodity, all from use table |
| Gcur2 | While interest payments could be disaggregated in proportions indicated by sources of income and personal taxes: interest, dividends, rental income, other property income by household income quintile from the CES, only data on the disaggregation of federal transfers could be found in the Congressional Budget Office's (CBO's) Distribution of Household Income and Federal Taxes (CBO, 2018). As data on state and local government transfers across household groups could not be found, this element was disaggregated in the proportions that would balance the SAM. |

| | |
|---|---|
| Inv | Change in private inventories by commodity from use table |
| Sd | Residuals that balanced the micro-SAMs |
| Cap1 | Nonresidential private fixed investment in structures by commodity + nonresidential private fixed investment in equipment by commodity + nonresidential private fixed investment in intellectual property products by commodity + residential private fixed investment by commodity + federal national defense: gross investment in structures by commodity + federal national defense: gross investment in equipment by commodity + federal national defense: gross investment in intellectual property products by commodity + federal national nondefense: gross investment in structures by commodity + federal national nondefense: gross investment in equipment by commodity + federal national nondefense: gross investment in intellectual property products by commodity + state and local: gross investment in structures by commodity + state and local: gross investment in equipment by commodity + state and local: gross investment in intellectual property products by commodity, all from use table |
| R1 | Exports of goods and services by commodity from use table |
| R2 | U.S. direct investment abroad, all U.S. parent companies, value added (gross product): by industry of U.S. parent company (BEA, 2018d), and value added by industry from use table when a BEA NIACS category spans more than one SAM NIACS category, as described in Chapter 4 |
| R3 | Money received from outside of the US: how many dollars received, from 2008 CPS immigration/emigration supplement, and household income quintile income limits from Census Bureau's historical income tables, as described in Chapter 4. |
| Tcom | Total commodity output by commodity + imports of goods and services by commodity, both from use table |
| Tind | Total industry output by commodity from use table |

| | |
|---|---|
| Tfac | F1 + F2 + F3 + F4 |
| Thcur | Personal income component used share of aggregate income received by each fifth of households (Census, 2018c). Consumption of fixed capital component used ‘housing: maintenance, repairs, insurance, other expenses’ category in CES. Domestic government social insurance component used distribution of payroll taxes across income groups from the CBO’s Distribution of Household Income and Federal Taxes. Transfer receipts from the rest of the world was as per R3. |

Notes: Table lists data sources and relevant calculations used to establish the proportions by which each element in the 2003, 2010 and 2016 US-macro SAMs was disaggregated to produce the 2003, 2010 and 2016 US micro-SAMs. As is usual with SAM compilation, the values of the macro-SAM elements were thus preserved, as one has greater confidence in national accounts data than other survey data. For brevity, the SAM elements are referred to using codes. A diagram of how codes map to SAM elements can be found in Figure 4.3 in Chapter 4.

Table B.3 – Data sources used to estimate proportions for alternatively disaggregating macro-SAM elements for the edu-SAM

| **SAM code for element being disaggregated** | **Data source** |
|---|---|
| I2 | First disaggregated into payments to labour, capital and taxes less subsidies using compensation of employees, gross operating surplus and taxes on production and imports less subsidies proportions in use table. Then these were disaggregated by industry using proportions indicated in use table. Labour payments from each industry were further disaggregated by labour factors using CPS data, as described in Chapter 4. Finally, totals across each labour factor category were reconciled with CPS data on distribution of total earnings across labour categories using the RAS procedure. |
| F1 | Same as before, except amendments to use of CPS data and household income quintile income limits from Census Bureau's historical income table, as described in Chapter 4. |
| F4 | Value added, net income and compensation of employees by majority-owned U.S. affiliates (BEA, 2018k). Then CPS, as described in Chapter 4. |
| R2 | All U.S. parent companies: value added, net income and compensation of employees (BEA, 2018l). Then CPS, as described in Chapter 4. |

Notes: Table lists data sources and relevant calculations used to establish the proportions by which some elements in the 2016-edu US-macro SAM were disaggregated to produce the 2016-edu US micro-SAM. All SAM elements not covered in this table, were disaggregated as described in Table B2. As is usual with SAM compilation, the values of the macro-SAM elements were preserved, as one has greater confidence in national accounts data than other survey data. For brevity, the SAM elements are referred to using codes. A diagram of how codes map to SAM elements can be found in Figure 4.3 in Chapter 4.

# Appendix E – Balanced United States (US) macro-social accounting matrices (SAMs)

Figure C.1 – 2003 US macro-SAM (in millions of current USD)

| | | | | | Current account | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | **Commodities** | **Industries** | **Factors** | **Households** | **Enterprises** | **Government** | **Inventories** | **Statistical discrepancy** | **Capital accounts** | **ROW** |
| **Commodities** | | | 8663168 | | 7723109 | | 1746986 | 14094 | 13660 | 2477183 | 1036177 |
| **Industries** | | 20135073 | | | | | | | | | |
| **Factors** | | | 11471910 | | | | | | -2 | | 353789 |
| **Current account** | **Households** | | | 6354054 | | 2815641 | 1383696 | | 2 | | 51431 |
| | **Enterprises** | | | 4419655 | 1219025 | | 365432 | | 1 | | 827 |
| | **Government** | | | 756559 | 815189 | 1670914 | | | | | 13920 |
| **Inventories** | | | | | | | | | | 14094 | |
| **Statistical discrepancy** | | | -5 | | 1 | -2 | 1 | | 5 | 13660 | |
| **Capital account** | | | | | 758069 | 1511900 | -278240 | | -5 | | |
| **ROW** | | 1539304 | | 295429 | 89431 | 6487 | 38707 | | -1 | -513213 | |
| **Totals** | | 21674377 | 20135073 | 11825697 | 10604824 | 6004940 | 3256582 | 14094 | 13660 | 1991724 | 1456144 |

Notes: Figure shows macro social accounting matrix (SAM) for the US in 2003. There are ten macro accounts: commodities, industries, factors, households, enterprises, government, inventories, capital account, rest-of-the-world (ROW) and statistical discrepancy. The SAM captures total monetary flows from column accounts to row accounts in 2003. For example, the industries account paid the commodities account $8,663,168 million in 2003. All amounts are expressed in 2003 USD. Totals are also shown for each account. An account's column total is equal to its row total, as all spending and saving must be financed. Grey cells contain no monetary flows.

Figure C.2 – 2010 US macro-SAM (in millions of current USD)

| | | | | | Current account | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | **Commodities** | **Industries** | **Factors** | **Households** | **Enterprises** | **Government** | **Inventories** | **Statistical discrepancy** | **Capital accounts** | **ROW** |
| **Commodities** | | | 11162500 | | 10185836 | | 2510143 | 53917 | -61037 | 2756059 | 1846280 |
| **Industries** | | 26093515 | | | | | | | | | |
| **Factors** | | | 14931015 | | | | | | 1 | | 715177 |
| **Current account** | **Households** | | | 7924936 | | 3599399 | 2407700 | | | | 76471 |
| | **Enterprises** | | | 6194534 | 1519205 | | 429500 | | | | -3655 |
| | **Government** | | | 1007266 | 1024026 | 2187734 | | | | | 22891 |
| **Inventories** | | | | | | | | | | 53917 | |
| **Statistical discrepancy** | | | | | | 1 | | | -1 | -61037 | |
| **Capital account** | | | | | 1137554 | 2350076 | -1175412 | | -1 | | |
| **ROW** | | 2360183 | | 519457 | 141885 | 2375 | 69985 | | 1 | -436722 | |
| **Totals** | | 28453698 | 26093515 | 15646193 | 14008506 | 8139584 | 4241917 | 53917 | -61037 | 2312217 | 2657164 |

Notes: Figure shows macro social accounting matrix (SAM) for the US in 2010. There are ten macro accounts: commodities, industries, factors, households, enterprises, government, inventories, capital account, rest-of-the-world (ROW) and statistical discrepancy. The SAM captures total monetary flows from column accounts to row accounts in 2010. For example, the industries account paid the commodities account $11,162,500 million in 2010. All amounts are expressed in 2010 USD. Totals are also shown for each account. An account's column total is equal to its row total, as all spending and saving must be financed. Grey cells contain no monetary flows.

Figure C.3 – 2016 US macro-SAM (in millions of current USD)

| | | Commodities | Industries | Factors | Current account | | | Inventories | Statistical discrepancy | Capital accounts | ROW |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Households | Enterprises | Government | | | | |
| Commodities | | | 13250812 | | 12766892 | | 2659488 | 28940 | 126923 | 3772438 | 2217576 |
| Industries | | 32084923 | | | | | | | | | |
| Factors | | | 18834113 | | | | | | | | 859128 |
| Current account | Households | | | 9956248 | | 5091785 | 2826808 | | | | 106450 |
| | Enterprises | | | 7851288 | 1289064 | | 531247 | | | | 2924 |
| | Government | | | 1241899 | 2278585 | 2155188 | | | | | 33531 |
| Inventories | | | | | | | | | | 28940 | |
| Statistical discrepancy | | | -2 | | 1 | -2 | | | 4 | 126923 | -1 |
| Capital account | | | | | 1458035 | 2408376 | -383936 | | -4 | | |
| ROW | | 2738146 | | 643806 | 188714 | 19176 | 75596 | | | -445830 | |
| Totals | | 34823069 | 32084923 | 19693241 | 17981291 | 9674523 | 5709203 | 28940 | 126923 | 3482471 | 3219608 |

Notes: Figure shows macro social accounting matrix (SAM) for the US in 2016. There are ten macro accounts: commodities, industries, factors, households, enterprises, government, inventories, capital account, rest-of-the-world (ROW) and statistical discrepancy. The SAM captures total monetary flows from column accounts to row accounts in 2016. For example, the industries account paid the commodities account $13,250,812 million in 2016. All amounts are expressed in 2016 USD. Totals are also shown for each account. An account's column total is equal to its row total, as all spending and saving must be financed. Grey cells contain no monetary flows.

# Appendix F – List of accounts in social accounting matrices (SAMs)

The SAMs are listed in alphabetical order, i.e. Alaska, Egypt, Ethiopia, India, Mexico, the United States (US), Vietnam and Zambia. SAM accounts are listed in alphabetical order within categories, specifically 'activities', 'commodities', 'factors of production', 'institutions' and 'other'. Where a SAM does not distinguish between activities and commodities, the category 'sectors' is used instead.

## Alaska

### Activities

| | | |
|---|---|---|
| Administration support services | Information | Professional services |
| Agriculture | Lodging | Real Estate |
| Air transportation | Management services | Refined petroleum |
| Construction | Mining services | Repair services |
| Eating and drinking | Miscellaneous | Seafood processing |
| Educational services | Oil and gas | State /local government services |
| Entertainment services | Other food manufacturing | Utilities |
| Federal government services | Other manufacturing | Waste management |
| Finance and insurance | Other mining | Water transportation |
| Fish harvesting | Other retail trade | Wholesale trade |
| Food stores | Other services | Wood products |
| Health services | Other transportation | |

### Commodities

| | | |
|---|---|---|
| Administration support services | Lodging | Professional services |
| Agriculture | Management services | Raw fish |
| Air transportation | Mining services | Real Estate |
| Construction | Miscellaneous | Refined petroleum |
| Eating and drinking | Oil and gas | Repair services |
| Educational services | Other food manufacturing | State /local government services |
| Entertainment services | Other manufacturing | Utilities |
| Federal government services | Other mining | Waste management |
| Finance and insurance | Other retail trade | Water transportation |
| Food stores | Other services | Wholesale trade |
| Health services | Other transportation | Wood products |
| Information | Processed seafood | |

### Factors of production

| | | |
|---|---|---|
| Capital | Labour - Health services | Labour - Other transportation |
| Labour - Administration support services | Labour - Information | Labour - Professional services |
| Labour - Agriculture | Labour - Lodging | Labour - Real Estate |
| Labour - Air transportation | Labour - Management services | Labour - Refined petroleum |
| Labour - Construction | Labour - Mining services | Labour - Repair services |
| Labour - Eating and drinking | Labour - Miscellaneous | Labour - Seafood processing |
| Labour - Educational services | Labour - Oil and gas | Labour - State /local government services |
| Labour - Entertainment services | Labour - Other food manufacturing | Labour - Utilities |
| Labour - Federal government services | Labour - Other manufacturing | Labour - Waste management |
| Labour - Finance and insurance | Labour - Other mining | Labour - Water transportation |
| Labour - Fish harvesting | Labour - Other retail trade | Labour - Wholesale trade |
| Labour - Food stores | Labour - Other services | Labour - Wood products |

### Institutions

| | | |
|---|---|---|
| Federal government | Low income households | State and local governments |
| High income households | Medium income households | |

### Other

| | | |
|---|---|---|
| Indirect taxes | Rest-of-the-world (ROW) capital account | Savings-investment account |
| Rest-of-the-US | Rest-of-the-world (ROW) current account | |

# Egypt

## Activities

| | | |
|---|---|---|
| Accommodation & food services | Finance and insurance | Other services |
| Agriculture | Fishery and aquaculture | Petroleum and products |
| Beverages | Grain milling, grain & other food products | Public administration |
| Business services | Health and social work | Real estate activities |
| Chemicals | Information & communication | Textiles |
| Clothing | Leather and footwear | Tobacco processing |
| Construction | Machinery and equipment | Transportation and storage |
| Crude oil and natural gas | Meat, fish, fruits, vegetables, oils & fats | Water |
| Dairy | Metals and metal products | Wholesale and retail trade |
| Education | Non-metal minerals | Wood and paper |
| Electricity | Other mining | |

## Commodities

| | | |
|---|---|---|
| Accommodation & food services | Finance and insurance | Other services |
| Agriculture | Fishery and aquaculture | Petroleum and products |
| Beverages | Grain milling, grain & other food products | Public administration |
| Business services | Health and social work | Real estate activities |
| Chemicals | Information & communication | Textiles |
| Clothing | Leather and footwear | Tobacco processing |
| Construction | Machinery and equipment | Transaction, transportation costs |
| Crude oil and natural gas | Meat, fish, fruits, vegetables, oils & fats | Transportation and storage |
| Dairy | Metals and metal products | Water |
| Education | Non-metal minerals | Wholesale and retail trade |
| Electricity | Other mining | Wood and paper |

## Factors of production

| | | |
|---|---|---|
| Capital | Semi-skilled labour | Unskilled labour |
| Land | Skilled labour | |

### Institutions

| | | |
|---|---|---|
| Enterprises | Household expenditure decile 2 | Household expenditure decile 6 |
| Government | Household expenditure decile 3 | Household expenditure decile 7 |
| Household expenditure decile 1 | Household expenditure decile 4 | Household expenditure decile 8 |
| Household expenditure decile 10 | Household expenditure decile 5 | Household expenditure decile 9 |

### Other

| | | |
|---|---|---|
| Direct taxes | Net sales taxes | Savings/Investment |
| Import tariffs | Rest-of-the-World (ROW) | Stock changes |

# Ethiopia

### Activities

| | | |
|---|---|---|
| Accommodation and food services | Fishing | Other mining |
| Agriculture | Forestry | Other services |
| Animal feed | Fruit and vegetable processing | Paper products and publishing |
| Beverages | Grain milling | Public administration |
| Business services | Health and social work | Real estate activities |
| Clothing | Information and communication | Sugar refining |
| Construction | Leather and footwear | Textiles |
| Dairy | Machinery and other equipment | Tobacco processing |
| Education | Meat processing | Transportation and storage |
| Electrical equipment | Metals and metal products | Vehicles and transport equipment |
| Electricity, gas and steam | Non-metal minerals | Water supply and sewage |
| Fats and oils | Other chemicals | Wholesale and retail trade |
| Finance and insurance | Other foods | Wood products |
| Fish and seafood processing | Other manufacturing | |

### Commodities

| | | |
|---|---|---|
| Accommodation and food services | Fish and seafood processing | Other mining |
| Agriculture | Fishing | Other services |
| Animal feed | Forestry | Paper products and publishing |
| Beverages | Fruit and vegetable processing | Petroleum products |
| Business services | Grain milling | Public administration |
| Clothing | Health and social work | Real estate activities |
| Coal and lignite | Information and communication | Sugar refining |
| Construction | Leather and footwear | Textiles |
| Dairy | Machinery and other equipment | Tobacco processing |
| Education | Meat processing | Transportation and storage |
| Electrical equipment | Metals and metal products | Vehicles and transport equipment |
| Electricity, gas and steam | Non-metal minerals | Water supply and sewage |
| Fats and oils | Other chemicals | Wholesale and retail trade |
| Fertilizers and herbicides | Other foods | Wood products |
| Finance and insurance | Other manufacturing | Other mining |
| Accommodation and food services | Fish and seafood processing | Other services |
| Agriculture | Fishing | Paper products and publishing |

| | | |
|---|---|---|
| Animal feed | Forestry | Petroleum products |
| Beverages | Fruit and vegetable processing | Public administration |
| Business services | Grain milling | Real estate activities |
| Clothing | Health and social work | Sugar refining |
| Coal and lignite | Information and communication | Textiles |
| Construction | Leather and footwear | Tobacco processing |
| Dairy | Machinery and other equipment | Transportation and storage |
| Education | Meat processing | Vehicles and transport equipment |
| Electrical equipment | Metals and metal products | Water supply and sewage |
| Electricity, gas and steam | Non-metal minerals | Wholesale and retail trade |
| Fats and oils | Other chemicals | Wood products |
| Fertilizers and herbicides | Other foods | |
| Finance and insurance | Other manufacturing | |

**Factors of production**

| | | |
|---|---|---|
| Capital - crops | Labour - rural secondary | Labour - urban tertiary |
| Capital - livestock | Labour - rural tertiary | Labour - urban uneducated |
| Capital - mining | Labour - rural uneducated | Land - agricultural crops |
| Capital - other | Labour - urban primary | |
| Labour - rural primary | Labour - urban secondary | |

**Institutions**

| | | |
|---|---|---|
| Enterprises | Household per capita expenditure quintile 2 | Household per capita expenditure quintile 5 |
| Government | Household per capita expenditure quintile 3 | |
| Household per capita expenditure quintile 1 | Household per capita expenditure quintile 4 | |

**Other**

| | | |
|---|---|---|
| Rest-of-the-World (ROW) | Taxes - direct | Taxes - sales |
| Savings-investment | Taxes - import | Transaction costs |

# India

## Sectors

| | | |
|---|---|---|
| Agriculture | Furniture & Fixture | Printing, publishing and allied activities |
| Air Transport | Hotel & Restaurants | Processed food |
| Banking and Insurance | Iron Ore | Public administration |
| Bauxite | Land Transport | Railways |
| Beverages | Leather and Leather Products | Real Estate |
| Business Service | Manganese | Rubber Products |
| Cement | Medical & Health | Storage & Warehouse |
| Chemicals | Metal Products | Sugar & Khandsari |
| Coal & Lignite | Metals | Supporting Services |
| Coal Tar Products | Natural Gas | Tea & Coffee Processing |
| Communication | Non-electrical Machinery | Textile Products |
| Construction | Non-metallic Mineral Products | Textiles |
| Copper | Non-Metallic Minerals | Tobacco Products |
| Crude Petroleum | Other Manufacturing | Trade |
| Education & Research | Other Metallic Minerals | Transport Equipment |
| Electrical Machinery | Other services | Vanaspati & Edible Oil |
| Electricity | Ownership of Dwelling | Water Supply |
| Fertilizer | Paper, paper products | Water Transport |
| Fishing | Petroleum Products | Wood & Wooden Product |
| Forestry & Logging | Plastic Products | |

## Factors of production

Capital

Labour is a collection of the following four indicators into the 48 possible combinations.

| | | | |
|---|---|---|---|
| Male | Female | | |
| Rural | Urban | | |
| Schedule Tribe | Schedule caste | Other caste | Others |
| Illiterate | Up to High School services | Graduate and above | |

### Institutions

| | | |
|---|---|---|
| Government | Household expenditure decile 4 | Household expenditure decile 9 |
| Household expenditure decile 1 | Household expenditure decile 5 | Private enterprises |
| Household expenditure decile 10 | Household expenditure decile 6 | Public enterprices |
| Household expenditure decile 2 | Household expenditure decile 7 | |
| Household expenditure decile 3 | Household expenditure decile 8 | |

### Other

| | | |
|---|---|---|
| Indirect taxes | Rest-of-the-world (ROW) | Savings-investment |

## Mexico

### Activities

| | | |
|---|---|---|
| Agriculture | Financial services | Paper and wood |
| Chemicals and oil refinery | Food processing | Public services |
| Commerce, transport and storage | Forestry, timber, fishing, hunting | Renting of dwellings |
| Communal and social services | Health services | Restaurants and hotels |
| Communication | Hydrocarbons | Services to firms |
| Construction | Metallic products, machinery, equipment | Textiles and leather products |
| Education | Mining | |
| Electricity, water and gas | Other private services | |

### Commodities

| | | |
|---|---|---|
| Agriculture | Financial services | Paper and wood |
| Chemicals and oil refinery | Food processing | Public services |
| Commerce, transport and storage | Forestry, timber, fishing, hunting | Renting of dwellings |
| Communal and social services | Health services | Restaurants and hotels |
| Communication | Hydrocarbons | Services to firms |
| Construction | Metallic products, machinery, equipment | Textiles and leather products |
| Education | Mining | |
| Electricity, water and gas | Other private services | |

### Factors of production

| | | |
|---|---|---|
| Capital | Labour, male, semi-skilled | Land - North and East Arid |
| Labour, female, semi-skilled | Labour, male, skilled | Land - Southern Humid |
| Labour, female, skilled | Labour, male, unskilled | Land - West Arid |
| Labour, female, unskilled | Land - Central High Arid | |

### Institutions

| | | |
|---|---|---|
| Household income decile 1 | Household income decile 5 | Household income decile 9 |
| Household income decile 2 | Household income decile 6 | Household income decile 10 |
| Household income decile 3 | Household income decile 7 | Enterprises |
| Household income decile 4 | Household income decile 8 | Government |

### Other

| | | |
|---|---|---|
| Direct taxes | Rest of world | Savings-investment |
| Import tariffs | Sales taxes | |

## United States (2003/2010/2016)

### Activities

| | | |
|---|---|---|
| Accommodation | Funds, trusts, and other financial vehicles | Performing arts, spectator sports, museums, and related activities |
| Administrative and support services | Furniture and related products | Petroleum and coal products |
| Air transportation | General merchandise stores | Pipeline transportation |
| Ambulatory health care services | Hospitals | Plastics and rubber products |
| Amusements, gambling, and recreation industries | Housing Services | Primary metals |
| Apparel and leather and allied products | Insurance carriers and related activities | Printing and related support activities |
| Broadcasting and telecommunications | Legal services | Publishing industries, except internet (includes software) |
| Chemical products | Machinery | Rail transportation |
| Computer and electronic products | Management of companies and enterprises | Rental and leasing services and lessors of intangible assets |
| Computer systems design and related services | Mining, except oil and gas | Securities, commodity contracts, and investments |
| Construction | Miscellaneous manufacturing | Social assistance |

| | | |
|---|---|---|
| Data processing, internet publishing, and other information services | Miscellaneous professional, scientific, and technical services | State and local general government |
| Educational services | Motion picture and sound recording industries | State and local government enterprises |
| Electrical equipment, appliances, and components | Motor vehicle and parts dealers | Support activities for mining |
| Fabricated metal products | Motor vehicles, bodies and trailers, and parts | Textile mills and textile product mills |
| Farms | Non-metallic mineral products | Transit and ground passenger transportation |
| Federal general government (defence) | Nursing and residential care facilities | Truck transportation |
| Federal general government (non-defence) | Oil and gas extraction | Utilities |
| Federal government enterprises | Other Real Estate | Warehousing and storage |
| Federal Reserve banks, credit intermediation, and related activities | Other retail | Waste management and remediation services |
| Food and beverage and tobacco products | Other services, except government | Water transportation |
| Food and beverage stores | Other transportation and support activities | Wholesale trade |
| Food services and drinking places | Other transportation equipment | Wood products |
| Forestry, fishing, and related activities | Paper products | |

**Commodities**

| | | |
|---|---|---|
| Accommodation | Furniture and related products | Petroleum and coal products |
| Administrative and support services | General merchandise stores | Pipeline transportation |
| Air transportation | Hospitals | Plastics and rubber products |
| Ambulatory health care services | Housing Services | Primary metals |
| Amusements, gambling, and recreation industries | Insurance carriers and related activities | Printing and related support activities |
| Apparel and leather and allied products | Legal services | Publishing industries, except internet (includes software) |
| Broadcasting and telecommunications | Machinery | Rail transportation |
| Chemical products | Management of companies and enterprises | Rental and leasing services and lessors of intangible assets |
| Computer and electronic products | Mining, except oil and gas | Scrap, used and second-hand goods |
| Computer systems design and related services | Miscellaneous manufacturing | Securities, commodity contracts, and investments |

| | | |
|---|---|---|
| Construction | Miscellaneous professional, scientific, and technical services | Social assistance |
| Data processing, internet publishing, and other information services | Motion picture and sound recording industries | State and local general government |
| Educational services | Motor vehicle and parts dealers | State and local government enterprises |
| Electrical equipment, appliances, and components | Motor vehicles, bodies and trailers, and parts | Support activities for mining |
| Fabricated metal products | Noncomparable imports and rest-of-the-world adjustment | Textile mills and textile product mills |
| Farms | Non-metallic mineral products | Transit and ground passenger transportation |
| Federal general government (defence) | Nursing and residential care facilities | Truck transportation |
| Federal general government (non-defence) | Oil and gas extraction | Utilities |
| Federal government enterprises | Other Real Estate | Warehousing and storage |
| Federal Reserve banks, credit intermediation, and related activities | Other retail | Waste management and remediation services |
| Food and beverage and tobacco products | Other services, except government | Water transportation |
| Food and beverage stores | Other transportation and support activities | Wholesale trade |
| Food services and drinking places | Other transportation equipment | Wood products |
| Forestry, fishing, and related activities | Paper products | |
| Funds, trusts, and other financial vehicles | Performing arts, spectator sports, museums, and related activities | |

### Factors of production

| | | |
|---|---|---|
| Value added: Accommodation | Value added: Funds, trusts, and other financial vehicles | Value added: Performing arts, spectator sports, museums, and related activities |
| Value added: Administrative and support services | Value added: Furniture and related products | Value added: Petroleum and coal products |
| Value added: Air transportation | Value added: General merchandise stores | Value added: Pipeline transportation |
| Value added: Ambulatory health care services | Value added: Hospitals | Value added: Plastics and rubber products |

| | | |
|---|---|---|
| Value added: Amusements, gambling, and recreation industries | Value added: Housing Services | Value added: Primary metals |
| Value added: Apparel and leather and allied products | Value added: Insurance carriers and related activities | Value added: Printing and related support activities |
| Value added: Broadcasting and telecommunications | Value added: Legal services | Value added: Publishing industries, except internet (includes software) |
| Value added: Chemical products | Value added: Machinery | Value added: Rail transportation |
| Value added: Computer and electronic products | Value added: Management of companies and enterprises | Value added: Rental and leasing services and lessors of intangible assets |
| Value added: Computer systems design and related services | Value added: Mining, except oil and gas | Value added: Securities, commodity contracts, and investments |
| Value added: Construction | Value added: Miscellaneous manufacturing | Value added: Social assistance |
| Value added: Data processing, internet publishing, and other information services | Value added: Miscellaneous professional, scientific, and technical services | Value added: State and local general government |
| Value added: Educational services | Value added: Motion picture and sound recording industries | Value added: State and local government enterprises |
| Value added: Electrical equipment, appliances, and components | Value added: Motor vehicle and parts dealers | Value added: Support activities for mining |
| Value added: Fabricated metal products | Value added: Motor vehicles, bodies and trailers, and parts | Value added: Textile mills and textile product mills |
| Value added: Farms | Value added: Non-metallic mineral products | Value added: Transit and ground passenger transportation |
| Value added: Federal general government (defence) | Value added: Nursing and residential care facilities | Value added: Truck transportation |
| Value added: Federal general government (non-defence) | Value added: Oil and gas extraction | Value added: Utilities |
| Value added: Federal government enterprises | Value added: Other Real Estate | Value added: Warehousing and storage |
| Value added: Federal Reserve banks, credit intermediation, and related activities | Value added: Other retail | Value added: Waste management and remediation services |
| Value added: Food and beverage and tobacco products | Value added: Other services, except government | Value added: Water transportation |
| Value added: Food and beverage stores | Value added: Other transportation and support activities | Value added: Wholesale trade |
| Value added: Food services and drinking places | Value added: Other transportation equipment | Value added: Wood products |
| Value added: Forestry, fishing, and related activities | Value added: Paper products | |

### Institutions

| | | |
|---|---|---|
| Enterprises | Household income quintile 2 | Household income quintile 5 |
| Government | Household income quintile 3 | |
| Household income quintile 1 | Household income quintile 4 | |

### Other

| | |
|---|---|
| Inventories | Savings-investment |
| Rest-of-the-world (ROW) | Statistical discrepancy |

## United States (2016-Edu)

Activities, commodities, institutions and other are the same as for the other US SAMs.

### Factors of production

| | | |
|---|---|---|
| Capital | Labour: Bachelor's degree or higher | Labour: Some college, no degree |
| Indirect taxes less subsidies | Labour: High school graduates, no college | |
| Labour: Associate degree | Labour: Less than a high school diploma | |

# Vietnam

## Activities

| | | |
|---|---|---|
| Agriculture | Fishery | Other mining |
| Air transport | Footwear | Other services |
| Alcoholic beverages | Forestry | Other transport |
| Aquaculture | Furniture | Paper products |
| Basic metals | Health | Petroleum products |
| Business services | Hotels and catering | Printing products |
| Cement | Leather products | Public administration |
| Clothing | Machinery and equipment | Real estate |
| Coal mining | Meat processing | Retail and wholesale trade |
| Communications | Metal products | Rice husking |
| Construction | Natural gas | Road transport |
| Crude oil | Non-alcoholic beverages | Textiles |
| Dairy | Non-metallic minerals | Tobacco processing |
| Education | Oils and fats processing | Vegetable and fruit processing |
| Electrical machinery | Other chemicals | Vehicles and transport equipment |
| Electricity and gas distribution | Other flours | Water distribution and utilities |
| Financial services | Other food processing | Wood products |
| Fish processing | Other manufacturing | Yarn and other fibres |

## Commodities

| | | |
|---|---|---|
| Agriculture | Fishery | Other services |
| Air transport | Footwear | Other transport |
| Alcoholic beverages | Forestry | Paper products |
| Aquaculture | Furniture | Petroleum products |
| Basic metals | Health | Printing products |
| Business services | Hotels and catering | Public administration |
| Cement | Leather products | Real estate |
| Clothing | Machinery and equipment | Retail and wholesale trade |
| Coal mining | Meat processing | Rice husking |
| Communications | Metal products | Road transport |
| Construction | Non-alcoholic beverages | Textiles |
| Crude oil | Non-metallic minerals | Tobacco processing |
| Dairy | Oils and fats processing | Vegetable and fruit processing |
| Education | Other chemicals | Vehicles and transport equipment |
| Electrical machinery | Other flours | Water distribution and utilities |
| Electricity and gas distribution | Other food processing | Wood products |
| Financial services | Other manufacturing | Yarn and other fibres |
| Fish processing | Other mining | |

### Factors of production

| | | |
|---|---|---|
| Agricultural capital | Labour - rural, secondary education | Labour - urban, tertiary education |
| Agricultural land | Labour - rural, tertiary education | Livestock |
| Fisheries capital | Labour - urban, primary education | Non-agricultural capital |
| Labour - rural, primary education | Labour - urban, secondary education | |

### Institutions

| | | |
|---|---|---|
| Agricultural enterprises | Household expenditure quintile 2 | Household expenditure quintile 5 |
| Government | Household expenditure quintile 3 | Non-agricultural enterprises |
| Household expenditure quintile 1 | Household expenditure quintile 4 | |

### Other

| | | |
|---|---|---|
| Activity taxes | Factor taxes | Sales taxes |
| Changes in stocks or inventories | Import tariffs | Savings-investment |
| Direct taxes | Rest-of-the-world (ROW) | Trade margins |

## Zambia

### Activities

| | | |
|---|---|---|
| Agriculture | Government administration | Other private services |
| Beverages | Grain milling | Petroleum |
| Business services | Health | Real estate |
| Chemicals | Hotels and catering | Retail and wholesale trade |
| Communication and post | Machinery and vehicles | Sugar refining |
| Construction | Meat, fish and dairy | Textiles and clothing |
| Education | Metals | Tobacco curing and processing |
| Electricity | Mining | Transport and storage |
| Financial services | Non-metals | Water |
| Fisheries | Other food processing | Wood and paper |
| Forestry | Other manufacturing | |

**Commodities**

| | | |
|---|---|---|
| Agriculture | Government administration | Other private services |
| Beverages | Grain milling | Petroleum |
| Business services | Health | Real estate |
| Chemicals | Hotels and catering | Retail and wholesale trade |
| Communication and post | Machinery and vehicles | Sugar refining |
| Construction | Meat, fish and dairy | Textiles and clothing |
| Education | Metals | Tobacco curing and processing |
| Electricity | Mining | Transport and storage |
| Financial services | Non-metals | Water |
| Fisheries | Other food processing | Wood and paper |
| Forestry | Other manufacturing | |

**Factors of production**

| | | |
|---|---|---|
| Capital | Labour - completed secondary | Livestock |
| Crop land | Labour - completed tertiary | |
| Labour - completed primary | Labour - not completed primary | |

**Institutions**

| | | |
|---|---|---|
| Enterprises | Household per capita expenditure quintile 2 | Household per capita expenditure quintile 5 |
| Government | Household per capita expenditure quintile 3 | |
| Household per capita expenditure quintile 1 | Household per capita expenditure quintile 4 | |

**Other**

| | | |
|---|---|---|
| Change in stocks | Taxes - Direct | Taxes - Sales |
| Rest-of-the-world (ROW) | Taxes - Export | Taxes - Value Added |
| Savings-Investment | Taxes - Import | Transaction costs |

# Appendix G – Climate Framework for Uncertainty, Negotiation and Distribution (FUND) estimated impacts by country, sector and Special Report on Emissions Scenarios (SRES) scenario

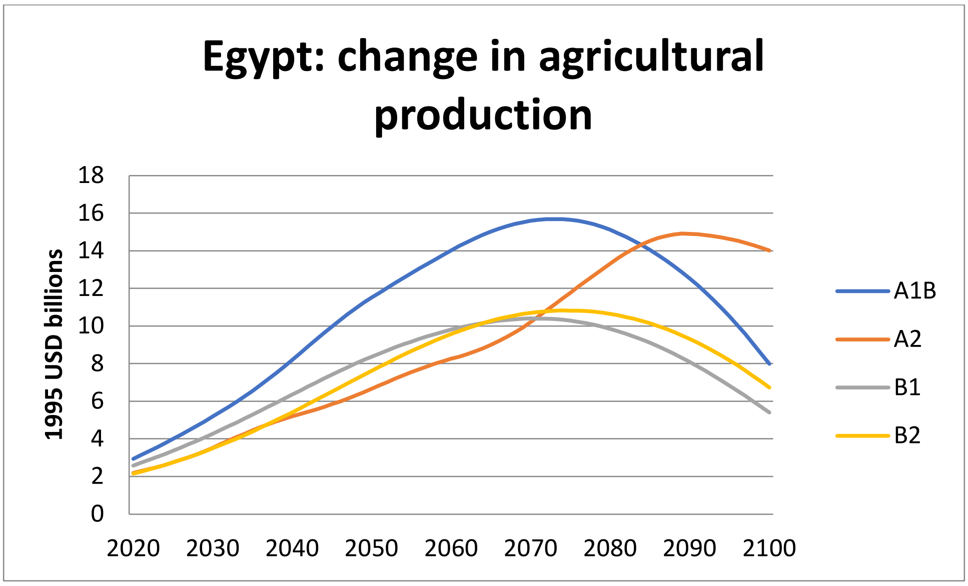



Figure G1: The figure shows the change in Egyptian agricultural production as a result of climate change, as estimated by FUND using the regional to national disaggregation process described in Chapter 6. Results are shown between 2020 and 2100, the time span of the FUND case study in Chapter 6. Changes are relative to a baseline in which there are no effects from climate change. Results were run for four SRES scenarios, A1B, A2, B1 and B2, and positive numbers represent increases in agricultural production. The results from the different scenarios are shown separately in the figure. FUND has three agricultural impact functions, which are dependent on the rate of climate change, the level of climate change, and $CO_2$ fertilisation respectively. The first and last of these are always negative and positive respectively, while level effects can be negative or positive depending on whether the regional temperature exceeds the specified optimal temperature for the given region. $CO_2$ fertilisation is a logarithmic function, so there are diminishing marginal benefits to increased $CO_2$. Agricultural production initially increases due to benefits from level and $CO_2$ fertilisation effects growing and outweighing the negative impacts from rate effects. Benefits to agricultural production from climate change peak and then start to decline when the optimal regional warming above preindustrial times is exceeded, so that level effects turn negative and slowly increasingly negate some of the benefits from $CO_2$ fertilisation. Impacts on agriculture were positive throughout the period, as $CO_2$ fertilisation benefits still dominated negative rate and level effects at 2100.

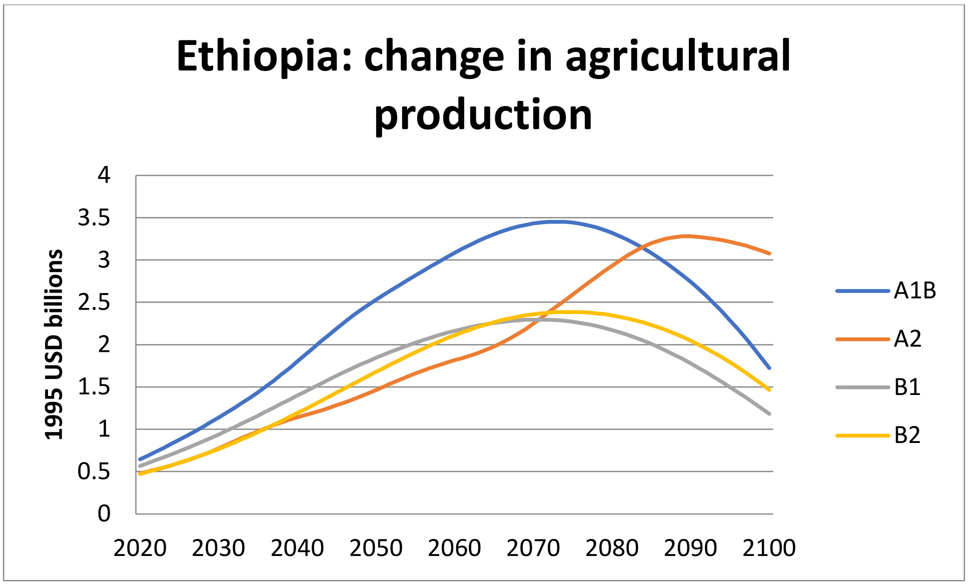



Figure G2: The figure shows the change in Ethiopian agricultural production as a result of climate change, as estimated by FUND using the regional to national disaggregation process described in Chapter 6. Results are shown between 2020 and 2100, the time span of the FUND case study in Chapter 6. Changes are relative to a baseline in which there are no effects from climate change. Results were run for four SRES scenarios, A1B, A2, B1 and B2, and positive numbers represent increases in agricultural production. The results from the different scenarios are shown separately in the figure. FUND has three agricultural impact functions, which are dependent on the rate of climate change, the level of climate change, and $CO_2$ fertilisation respectively. The first and last of these are always negative and positive respectively, while level effects can be negative or positive depending on whether the regional temperature exceeds the specified optimal temperature for the given region. $CO_2$ fertilisation is a logarithmic function, so there are diminishing marginal benefits to increased $CO_2$. Agricultural production initially increases due to benefits from level and $CO_2$ fertilisation effects growing and outweighing the negative impacts from rate effects. Benefits to agricultural production from climate change peak and then start to decline when the optimal regional warming above preindustrial times is exceeded, so that level effects turn negative and slowly increasingly negate some of the benefits from $CO_2$ fertilisation. Impacts on agriculture were positive throughout the period, as $CO_2$ fertilisation benefits still dominated negative rate and level effects at 2100.

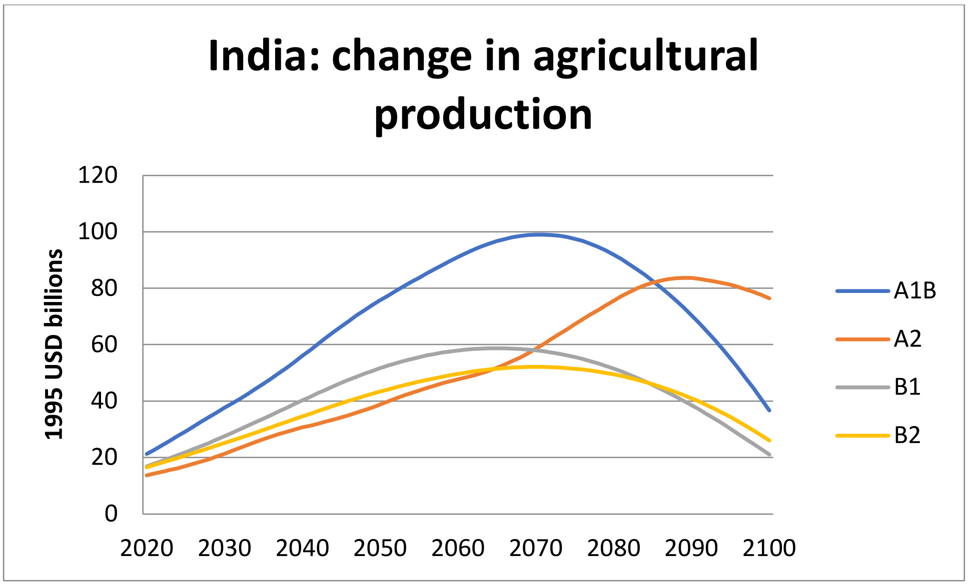



Figure G3: The figure shows the change in Indian agricultural production as a result of climate change, as estimated by FUND using the regional to national disaggregation process described in Chapter 6. Results are shown between 2020 and 2100, the time span of the FUND case study in Chapter 6. Changes are relative to a baseline in which there are no effects from climate change. Results were run for four SRES scenarios, A1B, A2, B1 and B2, and positive numbers represent increases in agricultural production. The results from the different scenarios are shown separately in the figure. FUND has three agricultural impact functions, which are dependent on the rate of climate change, the level of climate change, and $CO_2$ fertilisation respectively. The first and last of these are always negative and positive respectively, while level effects can be negative or positive depending on whether the regional temperature exceeds the specified optimal temperature for the given region. $CO_2$ fertilisation is a logarithmic function, so there are diminishing marginal benefits to increased $CO_2$. Agricultural production initially increases due to benefits from level and $CO_2$ fertilisation effects growing and outweighing the negative impacts from rate effects. Benefits to agricultural production from climate change peak and then start to decline when the optimal regional warming above preindustrial times is exceeded, so that level effects turn negative and slowly increasingly negate some of the benefits from $CO_2$ fertilisation. Impacts on agriculture were positive throughout the period, as $CO_2$ fertilisation benefits still dominated negative rate and level effects at 2100.

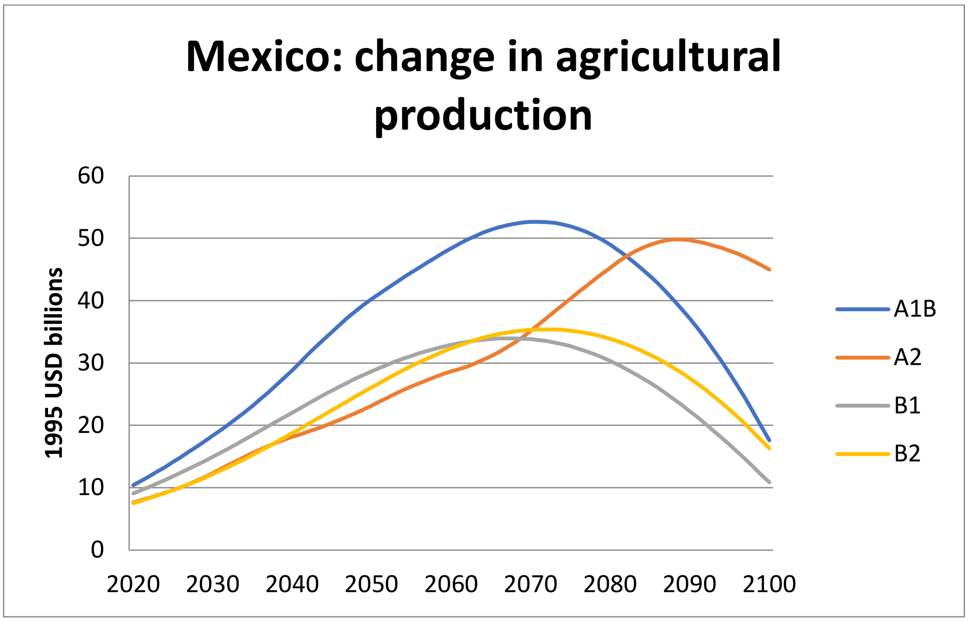



Figure G4: The figure shows the change in Mexican agricultural production as a result of climate change, as estimated by FUND using the regional to national disaggregation process described in Chapter 6. Results are shown between 2020 and 2100, the time span of the FUND case study in Chapter 6. Changes are relative to a baseline in which there are no effects from climate change. Results were run for four SRES scenarios, A1B, A2, B1 and B2, and positive numbers represent increases in agricultural production. The results from the different scenarios are shown separately in the figure. FUND has three agricultural impact functions, which are dependent on the rate of climate change, the level of climate change, and $CO_2$ fertilisation respectively. The first and last of these are always negative and positive respectively, while level effects can be negative or positive depending on whether the regional temperature exceeds the specified optimal temperature for the given region. $CO_2$ fertilisation is a logarithmic function, so there are diminishing marginal benefits to increased $CO_2$. Agricultural production initially increases due to benefits from level and $CO_2$ fertilisation effects growing and outweighing the negative impacts from rate effects. Benefits to agricultural production from climate change peak and then start to decline when the optimal regional warming above preindustrial times is exceeded, so that level effects turn negative and slowly increasingly negate some of the benefits from $CO_2$ fertilisation. Impacts on agriculture were positive throughout the period, as $CO_2$ fertilisation benefits still dominated negative rate and level effects at 2100.

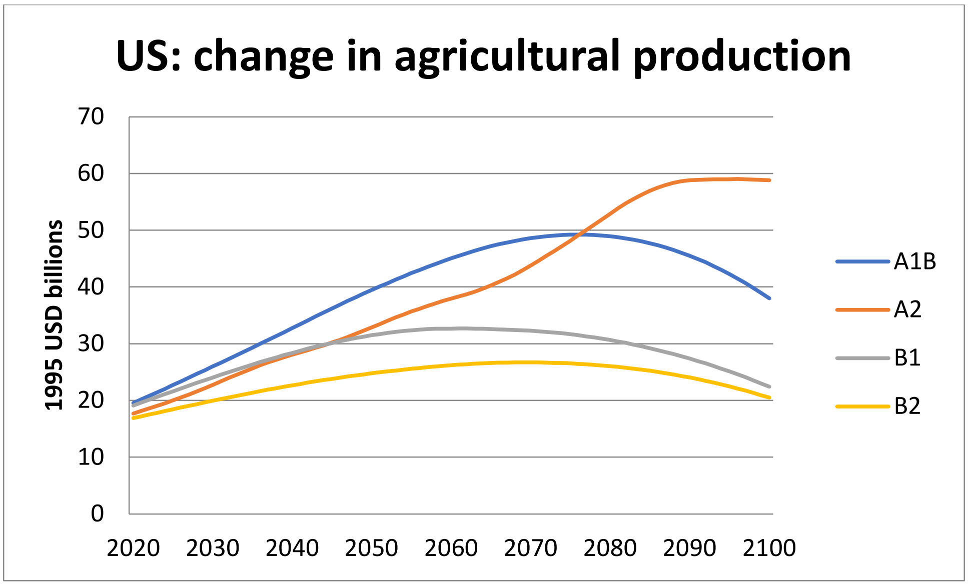



Figure G5: The figure shows the change in American agricultural production as a result of climate change, as estimated by FUND, between 2020 and 2100, the time span of the FUND case study in Chapter 6. Changes are relative to a baseline in which there are no effects from climate change. Results were run for four SRES scenarios, A1B, A2, B1 and B2, and positive numbers represent increases in agricultural production. The results from the different scenarios are shown separately in the figure. FUND has three agricultural impact functions, which are dependent on the rate of climate change, the level of climate change, and $CO_2$ fertilisation respectively. The first and last of these are always negative and positive respectively, while level effects can be negative or positive depending on whether the regional temperature exceeds the specified optimal temperature for the given region. $CO_2$ fertilisation is a logarithmic function, so there are diminishing marginal benefits to increased $CO_2$. Agricultural production initially increases due to benefits from level and $CO_2$ fertilisation effects growing and outweighing the negative impacts from rate effects. Benefits to agricultural production from climate change peak and then start to decline when the optimal regional warming above preindustrial times is exceeded, so that level effects turn negative and slowly increasingly negate some of the benefits from $CO_2$ fertilisation. Impacts on agriculture were positive throughout the period, as $CO_2$ fertilisation benefits still dominated negative rate and level effects at 2100.

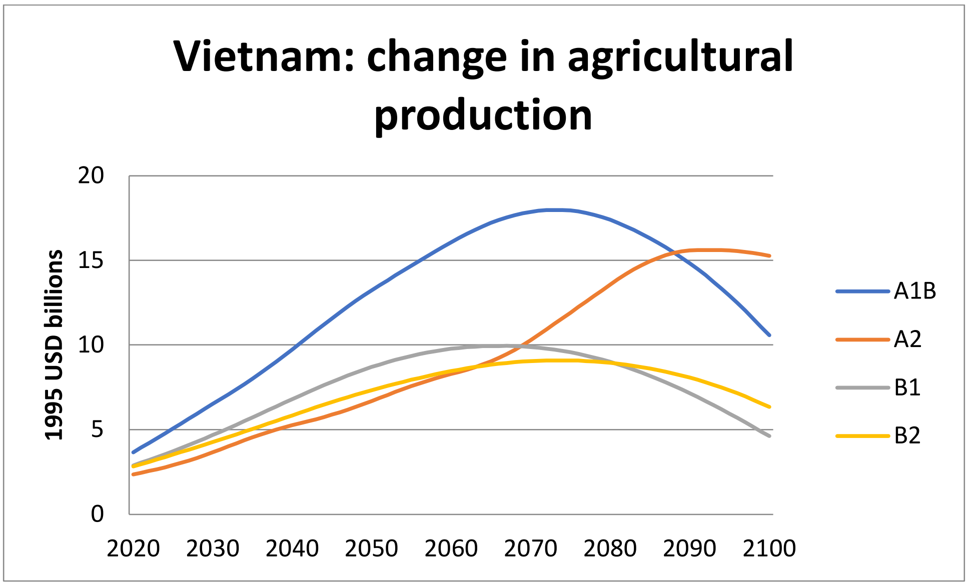



Figure G6: The figure shows the change in Vietnamese agricultural production as a result of climate change, as estimated by FUND using the regional to national disaggregation process described in Chapter 6. Results are shown between 2020 and 2100, the time span of the FUND case study in Chapter 6. Changes are relative to a baseline in which there are no effects from climate change. Results were run for four SRES scenarios, A1B, A2, B1 and B2, and positive numbers represent increases in agricultural production. The results from the different scenarios are shown separately in the figure. FUND has three agricultural impact functions, which are dependent on the rate of climate change, the level of climate change, and $CO_2$ fertilisation respectively. The first and last of these are always negative and positive respectively, while level effects can be negative or positive depending on whether the regional temperature exceeds the specified optimal temperature for the given region. $CO_2$ fertilisation is a logarithmic function, so there are diminishing marginal benefits to increased $CO_2$.

Agricultural production initially increases due to benefits from level and $CO_2$ fertilisation effects growing and outweighing the negative impacts from rate effects. Benefits to agricultural production from climate change peak and then start to decline when the optimal regional warming above preindustrial times is exceeded, so that level effects turn negative and slowly increasingly negate some of the benefits from $CO_2$ fertilisation. Impacts on agriculture were positive throughout the period, as $CO_2$ fertilisation benefits still dominated negative rate and level effects at 2100.

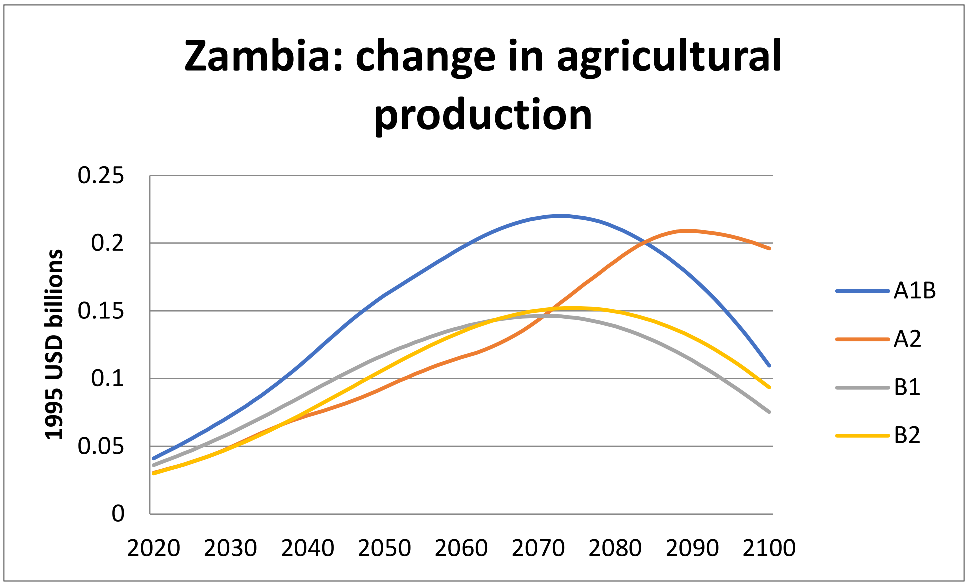



Figure G7: The figure shows the change in Zambian agricultural production as a result of climate change, as estimated by FUND using the regional to national disaggregation process described in Chapter 6. Results are shown between 2020 and 2100, the time span of the FUND case study in Chapter 6. Changes are relative to a baseline in which there are no effects from climate change. Results were run for four SRES scenarios, A1B, A2, B1 and B2, and positive numbers represent increases in agricultural production. The results from the different scenarios are shown separately in the figure. FUND has three agricultural impact functions, which are dependent on the rate of climate change, the level of climate change, and $CO_2$ fertilisation respectively. The first and last of these are always negative and positive respectively, while level effects can be negative or positive depending on whether the regional temperature exceeds the specified optimal temperature for the given region. $CO_2$ fertilisation is a logarithmic function, so there are diminishing marginal benefits to increased $CO_2$. Agricultural production initially increases due to benefits from level and $CO_2$ fertilisation effects growing and outweighing the negative impacts from rate effects. Benefits to agricultural production from climate change peak and then start to decline when the optimal regional warming above preindustrial times is exceeded, so that level effects turn negative and slowly increasingly negate some of the benefits from $CO_2$ fertilisation. Impacts on agriculture were positive throughout the period, as $CO_2$ fertilisation benefits still dominated negative rate and level effects at 2100.

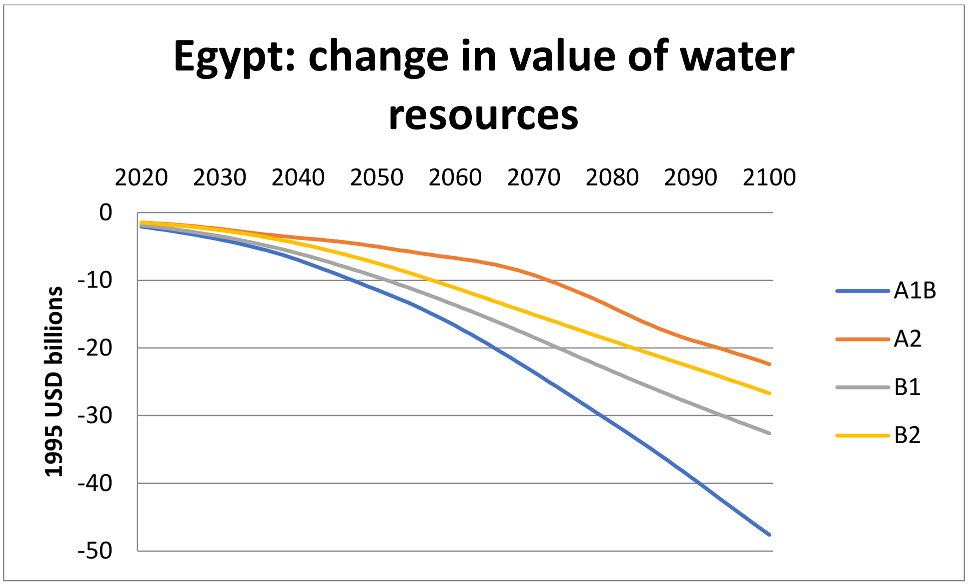



Figure G8: The figure shows the change in Egyptian water utility output as a result of climate change, as estimated by FUND using the regional to national disaggregation process described in Chapter 6. Results are shown between 2020 and 2100, the time span of the FUND case study in Chapter 6. Changes are relative to a baseline in which there are no effects from climate change. Results were run for four SRES scenarios, A1B, A2, B1 and B2, and negative numbers represent decreases in water utility output. The results from the different scenarios are shown separately in the figure. For a global mean surface temperature (GMST) higher than the preindustrial level, the FUND water impact function always produces negative impacts, with impacts becoming more negative the higher GMST is above the preindustrial level.

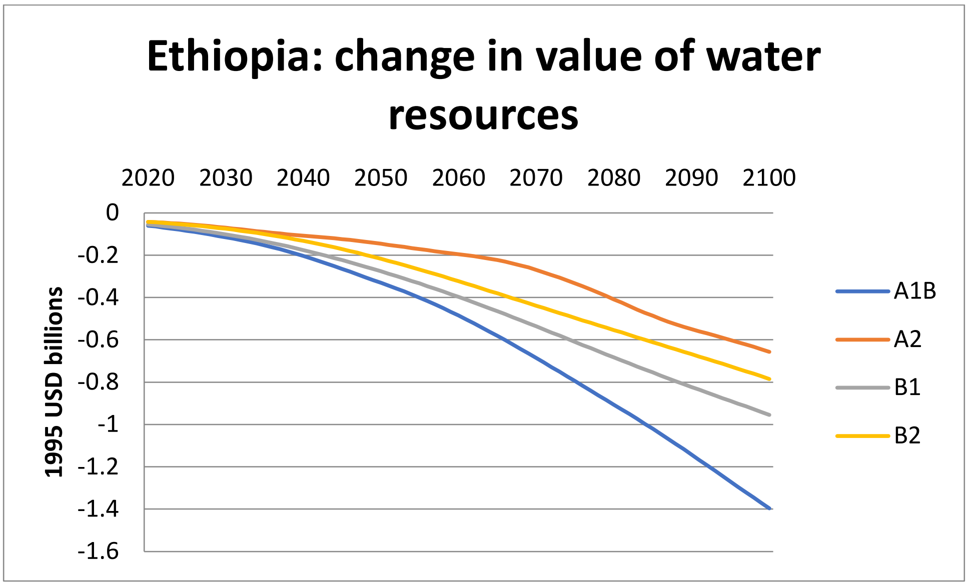



Figure G9: The figure shows the change in Ethiopian water utility output as a result of climate change, as estimated by FUND using the regional to national disaggregation process described in Chapter 6. Results are shown between 2020 and 2100, the time span of the FUND case study in Chapter 6. Changes are relative to a baseline in which there are no effects from climate change. Results were run for four SRES scenarios, A1B, A2, B1 and B2, and negative numbers represent decreases in water utility output. The results from the different scenarios are shown separately in the figure. For a global mean surface temperature (GMST) higher than the preindustrial level, the FUND water impact function always produces negative impacts, with impacts becoming more negative the higher GMST is above the preindustrial level.

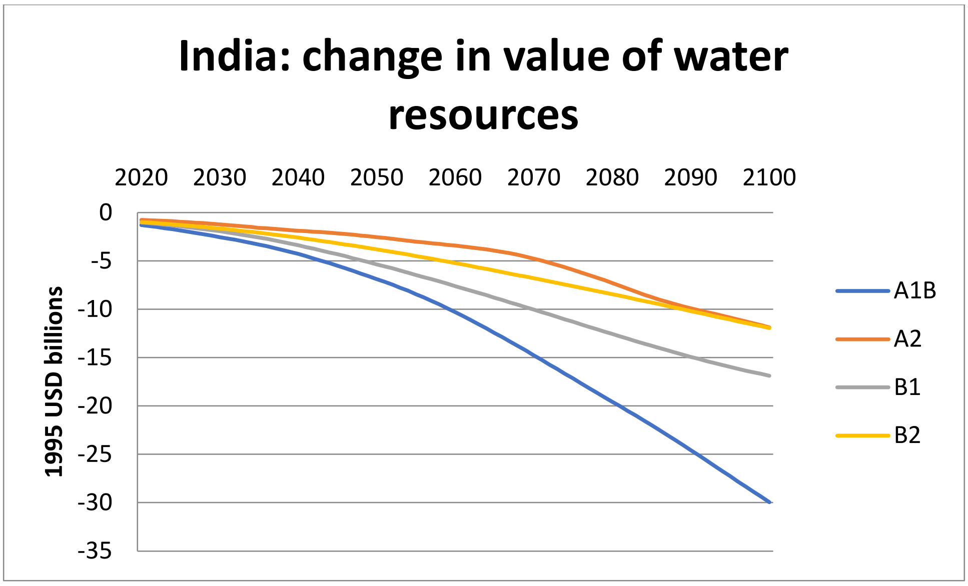



Figure G10: The figure shows the change in Indian water utility output as a result of climate change, as estimated by FUND using the regional to national disaggregation process described in Chapter 6. Results are shown between 2020 and 2100, the time span of the FUND case study in Chapter 6. Changes are relative to a baseline in which there are no effects from climate change. Results were run for four SRES scenarios, A1B, A2, B1 and B2, and negative numbers represent decreases in water utility output. The results from the different scenarios are shown separately in the figure. For a global mean surface temperature (GMST) higher than the preindustrial level, the FUND water impact function always produces negative impacts, with impacts becoming more negative the higher GMST is above the preindustrial level.

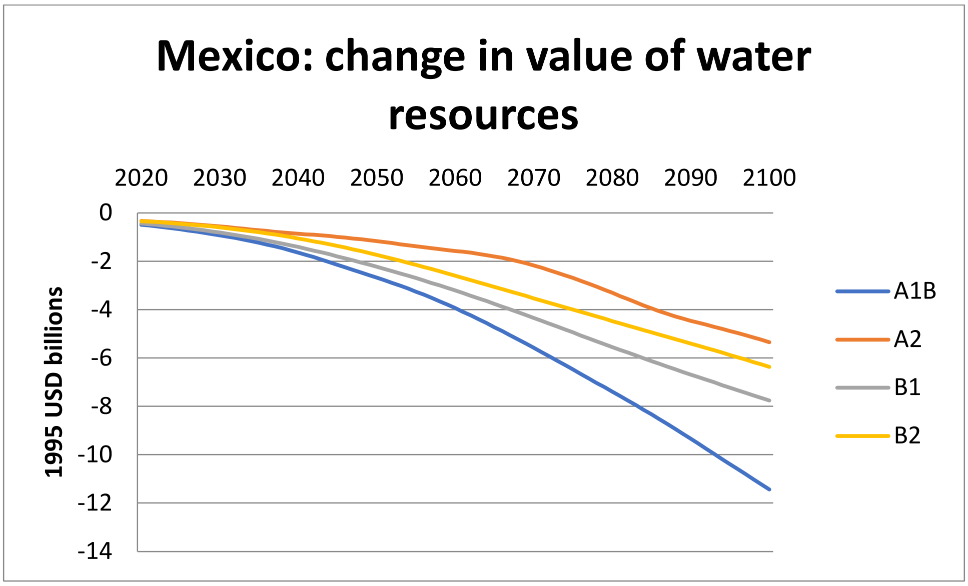



Figure G11: The figure shows the change in Mexican water utility output as a result of climate change, as estimated by FUND using the regional to national disaggregation process described in Chapter 6. Results are shown between 2020 and 2100, the time span of the FUND case study in Chapter 6. Changes are relative to a baseline in which there are no effects from climate change. Results were run for four SRES scenarios, A1B, A2, B1 and B2, and negative numbers represent decreases in water utility output. The results from the different scenarios are shown separately in the figure. For a global mean surface temperature (GMST) higher than the preindustrial level, the FUND water impact function always produces negative impacts, with impacts becoming more negative the higher GMST is above the preindustrial level.

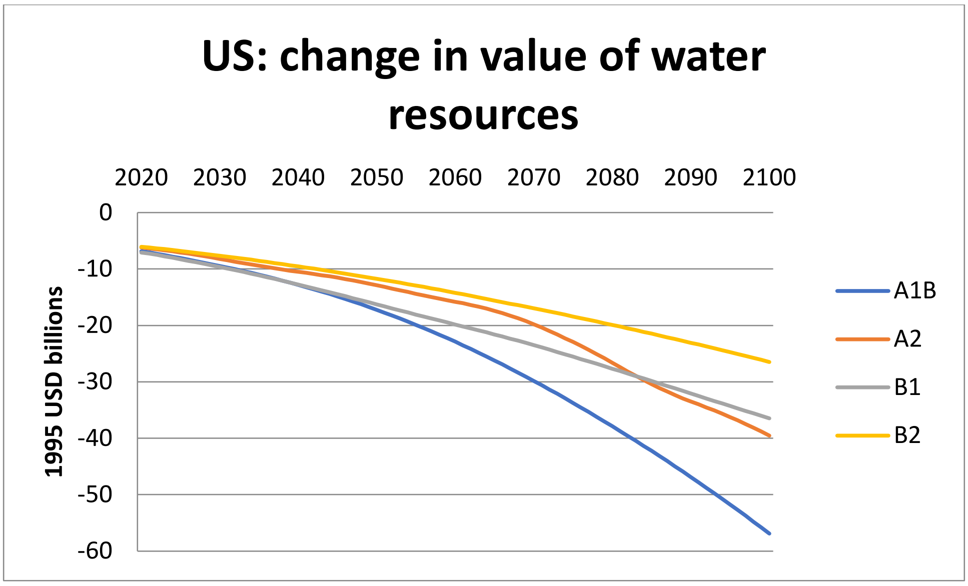



Figure G12: The figure shows the change in American water utility output as a result of climate change, as estimated by FUND, between 2020 and 2100, the time span of the FUND case study in Chapter 6. Changes are relative to a baseline in which there are no effects from climate change. Results were run for four SRES scenarios, A1B, A2, B1 and B2, and negative numbers represent decreases in water utility output. The results from the different scenarios are shown separately in the figure. For a global mean surface temperature (GMST) higher than the preindustrial level, the FUND water impact function always produces negative impacts, with impacts becoming more negative the higher GMST is above the preindustrial level.

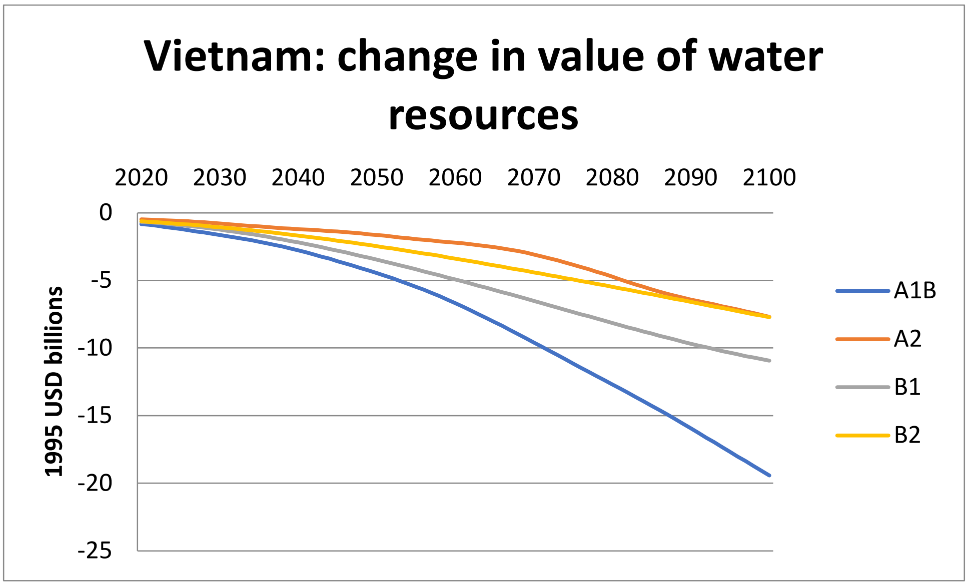



Figure G13: The figure shows the change in Vietnamese water utility output as a result of climate change, as estimated by FUND using the regional to national disaggregation process described in Chapter 6. Results are shown between 2020 and 2100, the time span of the FUND case study in Chapter 6. Changes are relative to a baseline in which there are no effects from climate change. Results were run for four SRES scenarios, A1B, A2, B1 and B2, and negative numbers represent decreases in water utility output. The results from the different scenarios are shown separately in the figure. For a global mean surface temperature (GMST) higher than the preindustrial level, the FUND water impact function always produces negative impacts, with impacts becoming more negative the higher GMST is above the preindustrial level.

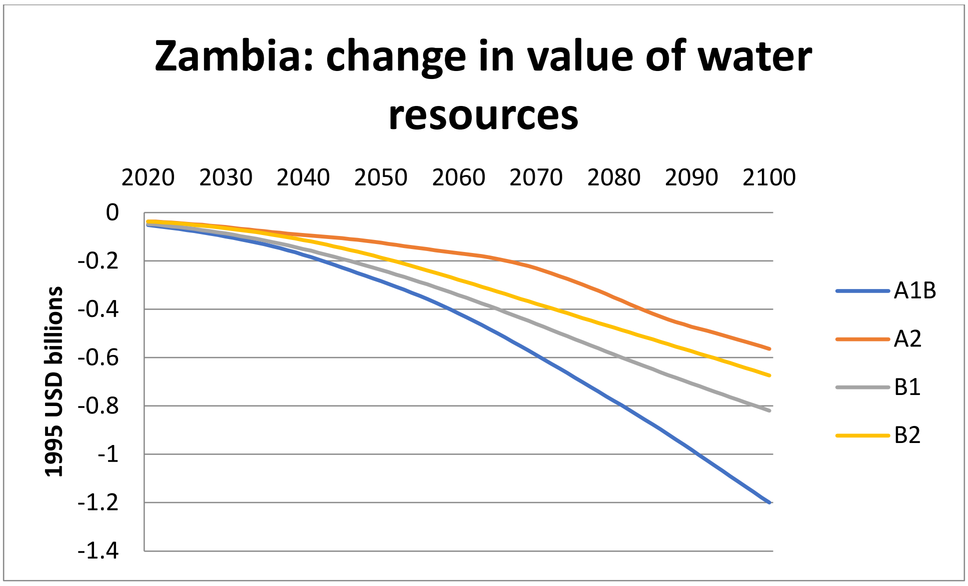



Figure G14: The figure shows the change in Zambian water utility output as a result of climate change, as estimated by FUND using the regional to national disaggregation process described in Chapter 6. Results are shown between 2020 and 2100, the time span of the FUND case study in Chapter 6. Changes are relative to a baseline in which there are no effects from climate change. Results were run for four SRES scenarios, A1B, A2, B1 and B2, and negative numbers represent decreases in water utility output. The results from the different scenarios are shown separately in the figure. For a global mean surface temperature (GMST) higher than the preindustrial level, the FUND water impact function always produces negative impacts, with impacts becoming more negative the higher GMST is above the preindustrial level.

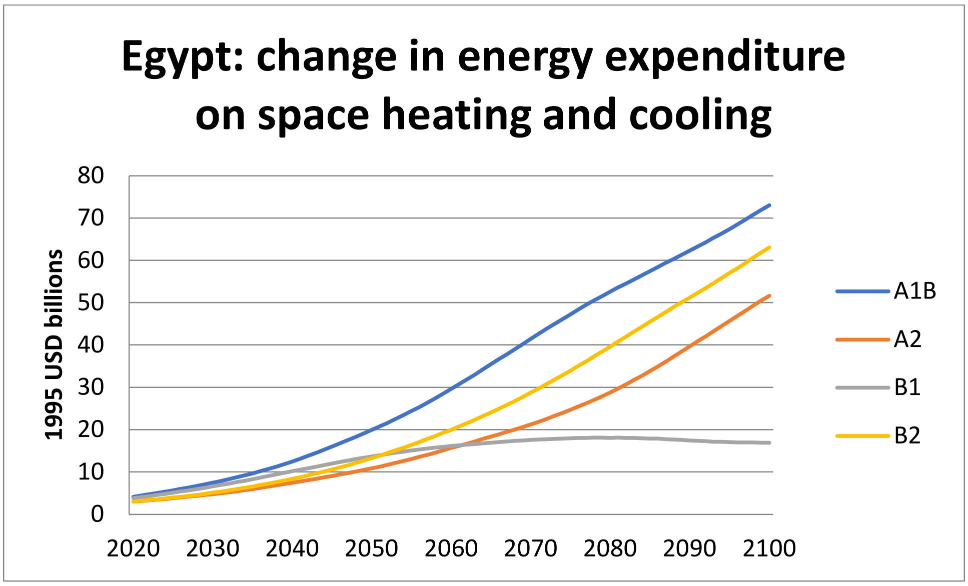



Figure G15: The figure shows the change in Egyptian demand for energy as a result of climate change, as estimated by FUND using the regional to national disaggregation process described in Chapter 6. Results are shown between 2020 and 2100, the time span of the FUND case study in Chapter 6. Changes are relative to a baseline in which there are no effects from climate change. Results were run for four SRES scenarios, A1B, A2, B1 and B2, and positive (negative) numbers represent increases (decreases) in demand for energy. The results from the different scenarios are shown separately in the figure. FUND models changes in energy demand for space heating and cooling separately. Savings from reduced space heating display decreasing marginal benefits from temperature rises, which saturate. The costs of increased space cooling, however, do not saturate. Demand for energy increases if the costs of increased space cooling exceed the savings from reduced space heating. Demand for energy decreases if the savings from reduced space heating exceed the costs of increased space cooling. The balance of savings and costs is different at different temperatures. As savings from reduced space heating saturate, whereas costs from increased space cooling do not, then, all other things being equal, demand for energy will increase at higher temperatures. However, the heating and cooling demand functions also depend on growth in income per capita, population growth and autonomous energy efficiency improvement, which is why energy demand begins to dip in the B1 scenario towards the end of the century. Note that an increase (decrease) in energy demand did not necessarily have a positive (negative) effect on the economy, as a budget constraint was imposed, as described in Chapter 6, to ensure that increases in expenditures didn't automatically increase economic growth. An increase (decrease) in expenditure was thus funded through decreased (increased) expenditure on other goods and services, so that households' total spending remained constant.

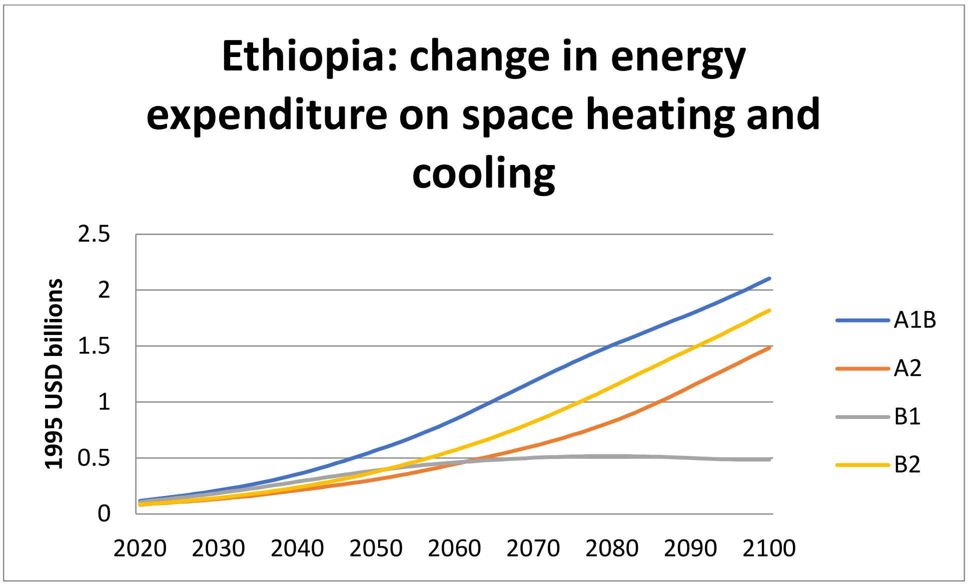



Figure G16: The figure shows the change in Ethiopian demand for energy as a result of climate change, as estimated by FUND using the regional to national disaggregation process described in Chapter 6. Results are shown between 2020 and 2100, the time span of the FUND case study in Chapter 6. Changes are relative to a baseline in which there are no effects from climate change. Results were run for four SRES scenarios, A1B, A2, B1 and B2, and positive (negative) numbers represent increases (decreases) in demand for energy. The results from the different scenarios are shown separately in the figure. FUND models changes in energy demand for space heating and cooling separately. Savings from reduced space heating display decreasing marginal benefits from temperature rises, which saturate. The costs of increased space cooling, however, do not saturate. Demand for energy increases if the costs of increased space cooling exceed the savings from reduced space heating. Demand for energy decreases if the savings from reduced space heating exceed the costs of increased space cooling. The balance of savings and costs is different at different temperatures. As savings from reduced space heating saturate, whereas costs from increased space cooling do not, then, all other things being equal, demand for energy will increase at higher temperatures. However, the heating and cooling demand functions also depend on growth in income per capita, population growth and autonomous energy efficiency improvement, which is why energy demand begins to dip in the B1 scenario towards the end of the century. Note that an increase (decrease) in energy demand did not necessarily have a positive (negative) effect on the economy, as a budget constraint was imposed, as described in Chapter 6, to ensure that increases in expenditures didn't automatically increase economic growth. An increase (decrease) in expenditure was thus funded through decreased (increased) expenditure on other goods and services, so that households' total spending remained constant.

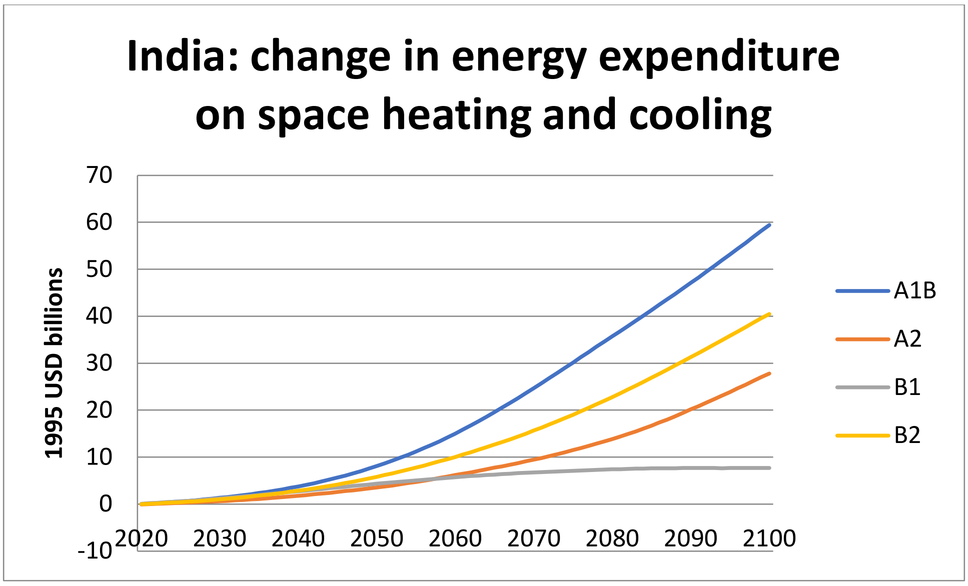



Figure G17: The figure shows the change in Indian demand for energy as a result of climate change, as estimated by FUND using the regional to national disaggregation process described in Chapter 6. Results are shown between 2020 and 2100, the time span of the FUND case study in Chapter 6. Changes are relative to a baseline in which there are no effects from climate change. Results were run for four SRES scenarios, A1B, A2, B1 and B2, and positive (negative) numbers represent increases (decreases) in demand for energy. The results from the different scenarios are shown separately in the figure. FUND models changes in energy demand for space heating and cooling separately. Savings from reduced space heating display decreasing marginal benefits from temperature rises, which saturate. The costs of increased space cooling, however, do not saturate. Demand for energy increases if the costs of increased space cooling exceed the savings from reduced space heating. Demand for energy decreases if the savings from reduced space heating exceed the costs of increased space cooling. The balance of savings and costs is different at different temperatures. As savings from reduced space heating saturate, whereas costs from increased space cooling do not, then, all other things being equal, demand for energy will increase at higher temperatures. However, the heating and cooling demand functions also depend on growth in income per capita, population growth and autonomous energy efficiency improvement, which is why energy demand begins to dip in the B1 scenario towards the end of the century. Note that an increase (decrease) in energy demand did not necessarily have a positive (negative) effect on the economy, as a budget constraint was imposed, as described in Chapter 6, to ensure that increases in expenditures didn't automatically increase economic growth. An increase (decrease) in expenditure was thus funded through decreased (increased) expenditure on other goods and services, so that households' total spending remained constant.

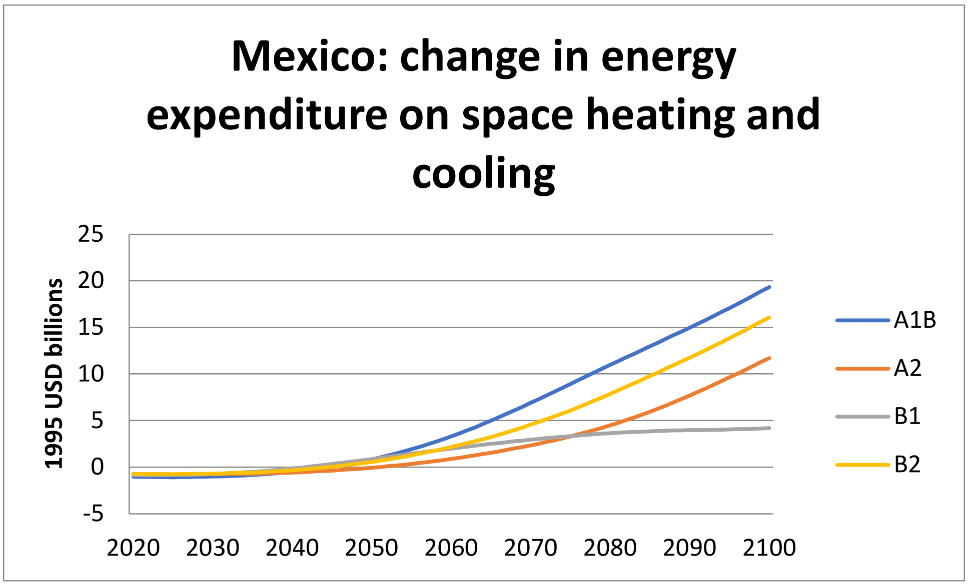



Figure G18: The figure shows the change in Mexican demand for energy as a result of climate change, as estimated by FUND using the regional to national disaggregation process described in Chapter 6. Results are shown between 2020 and 2100, the time span of the FUND case study in Chapter 6. Changes are relative to a baseline in which there are no effects from climate change. Results were run for four SRES scenarios, A1B, A2, B1 and B2, and positive (negative) numbers represent increases (decreases) in demand for energy. The results from the different scenarios are shown separately in the figure. FUND models changes in energy demand for space heating and cooling separately. Savings from reduced space heating display decreasing marginal benefits from temperature rises, which saturate. The costs of increased space cooling, however, do not saturate. Demand for energy increases if the costs of increased space cooling exceed the savings from reduced space heating. Demand for energy decreases if the savings from reduced space heating exceed the costs of increased space cooling. The balance of savings and costs is different at different temperatures. As savings from reduced space heating saturate, whereas costs from increased space cooling do not, then, all other things being equal, demand for energy will increase at higher temperatures. However, the heating and cooling demand functions also depend on growth in income per capita, population growth and autonomous energy efficiency improvement. Note that an increase (decrease) in energy demand did not necessarily have a positive (negative) effect on the economy, as a budget constraint was imposed, as described in Chapter 6, to ensure that increases in expenditures didn't automatically increase economic growth. An increase (decrease) in expenditure was thus funded through decreased (increased) expenditure on other goods and services, so that households' total spending remained constant.

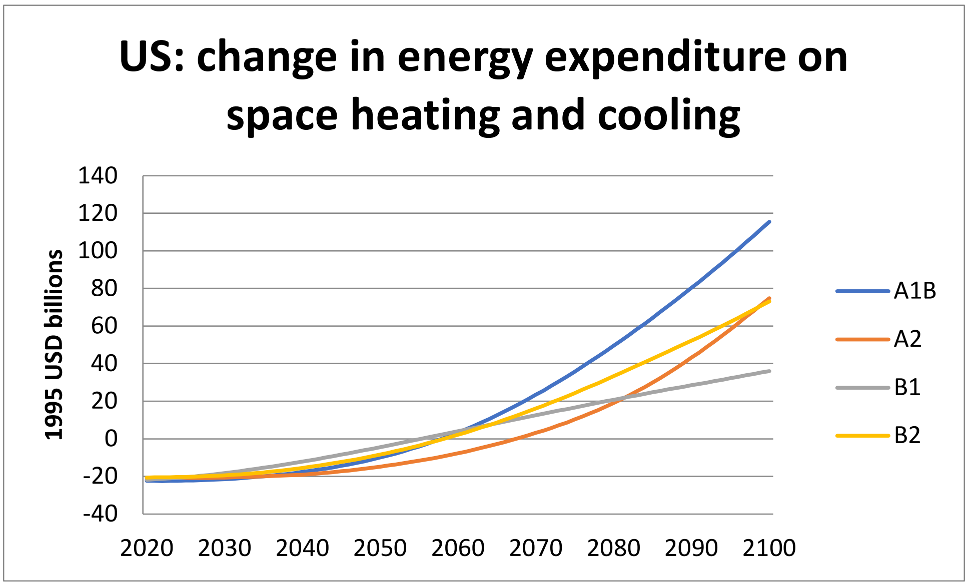



Figure G19: The figure shows the change in American demand for energy as a result of climate change, as estimated by FUND, between 2020 and 2100, the time span of the FUND case study in Chapter 6. Changes are relative to a baseline in which there are no effects from climate change. Results were run for four SRES scenarios, A1B, A2, B1 and B2, and positive (negative) numbers represent increases (decreases) in demand for energy. The results from the different scenarios are shown separately in the figure. FUND models changes in energy demand for space heating and cooling separately. Savings from reduced space heating display decreasing marginal benefits from temperature rises, which saturate. The costs of increased space cooling, however, do not saturate. Demand for energy increases if the costs of increased space cooling exceed the savings from reduced space heating. Demand for energy decreases if the savings from reduced space heating exceed the costs of increased space cooling. The balance of savings and costs is different at different temperatures. As savings from reduced space heating saturate, whereas costs from increased space cooling do not, then, all other things being equal, demand for energy will increase at higher temperatures. However, the heating and cooling demand functions also depend on growth in income per capita, population growth and autonomous energy efficiency improvement. Note that an increase (decrease) in energy demand did not necessarily have a positive (negative) effect on the economy, as a budget constraint was imposed, as described in Chapter 6, to ensure that increases in expenditures didn't automatically increase economic growth. An increase (decrease) in expenditure was thus funded through decreased (increased) expenditure on other goods and services, so that households' total spending remained constant.

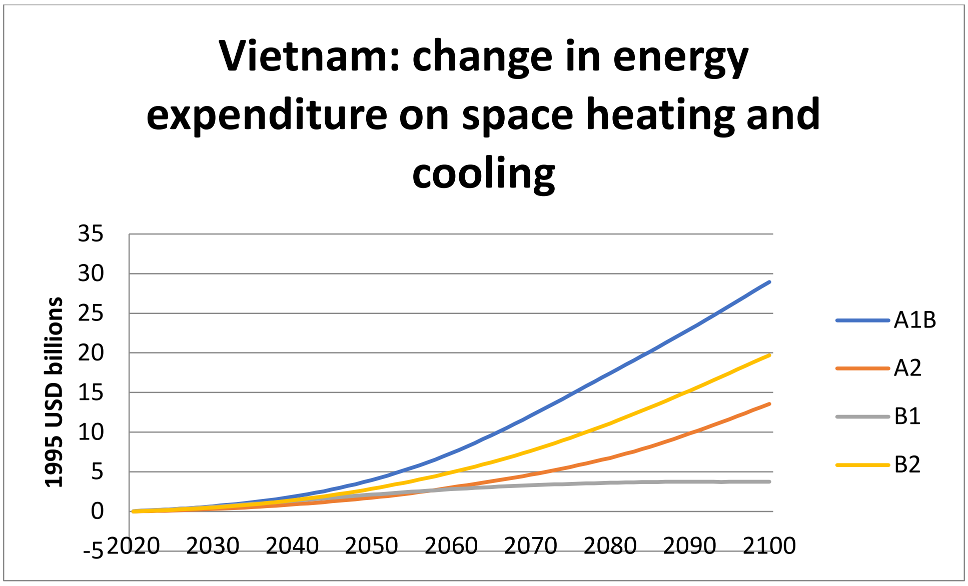



Figure G20: The figure shows the change in Vietnamese demand for energy as a result of climate change, as estimated by FUND using the regional to national disaggregation process described in Chapter 6. Results are shown between 2020 and 2100, the time span of the FUND case study in Chapter 6. Changes are relative to a baseline in which there are no effects from climate change. Results were run for four SRES scenarios, A1B, A2, B1 and B2, and positive (negative) numbers represent increases (decreases) in demand for energy. The results from the different scenarios are shown separately in the figure. FUND models changes in energy demand for space heating and cooling separately. Savings from reduced space heating display decreasing marginal benefits from temperature rises, which saturate. The costs of increased space cooling, however, do not saturate. Demand for energy increases if the costs of increased space cooling exceed the savings from reduced space heating. Demand for energy decreases if the savings from reduced space heating exceed the costs of increased space cooling. The balance of savings and costs is different at different temperatures. As savings from reduced space heating saturate, whereas costs from increased space cooling do not, then, all other things being equal, demand for energy will increase at higher temperatures. However, the heating and cooling demand functions also depend on growth in income per capita, population growth and autonomous energy efficiency improvement, which is why energy demand begins to dip in the B1 scenario towards the end of the century. Note that an increase (decrease) in energy demand did not necessarily have a positive (negative) effect on the economy, as a budget constraint was imposed, as described in Chapter 6, to ensure that increases in expenditures didn't automatically increase economic growth. An increase (decrease) in expenditure was thus funded through decreased (increased) expenditure on other goods and services, so that households' total spending remained constant.

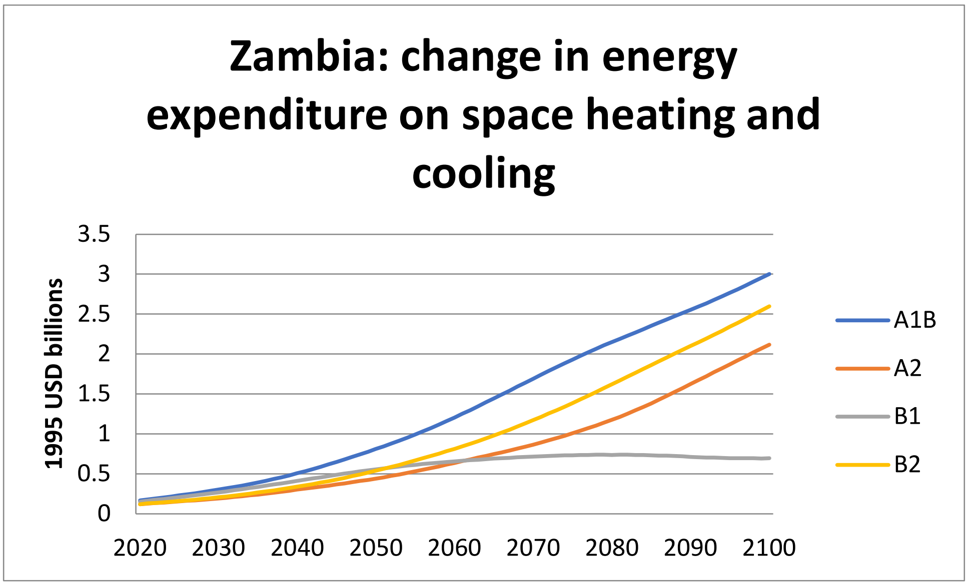



Figure G21: The figure shows the change in Zambian demand for energy as a result of climate change, as estimated by FUND using the regional to national disaggregation process described in Chapter 6. Results are shown between 2020 and 2100, the time span of the FUND case study in Chapter 6. Changes are relative to a baseline in which there are no effects from climate change. Results were run for four SRES scenarios, A1B, A2, B1 and B2, and positive (negative) numbers represent increases (decreases) in demand for energy. The results from the different scenarios are shown separately in the figure. FUND models changes in energy demand for space heating and cooling separately. Savings from reduced space heating display decreasing marginal benefits from temperature rises, which saturate. The costs of increased space cooling, however, do not saturate. Demand for energy increases if the costs of increased space cooling exceed the savings from reduced space heating. Demand for energy decreases if the savings from reduced space heating exceed the costs of increased space cooling. The balance of savings and costs is different at different temperatures. As savings from reduced space heating saturate, whereas costs from increased space cooling do not, then, all other things being equal, demand for energy will increase at higher temperatures. However, the heating and cooling demand functions also depend on growth in income per capita, population growth and autonomous energy efficiency improvement, which is why energy demand begins to dip in the B1 scenario towards the end of the century. Note that an increase (decrease) in energy demand did not necessarily have a positive (negative) effect on the economy, as a budget constraint was imposed, as described in Chapter 6, to ensure that increases in expenditures didn't automatically increase economic growth. An increase (decrease) in expenditure was thus funded through decreased (increased) expenditure on other goods and services, so that households' total spending remained constant.

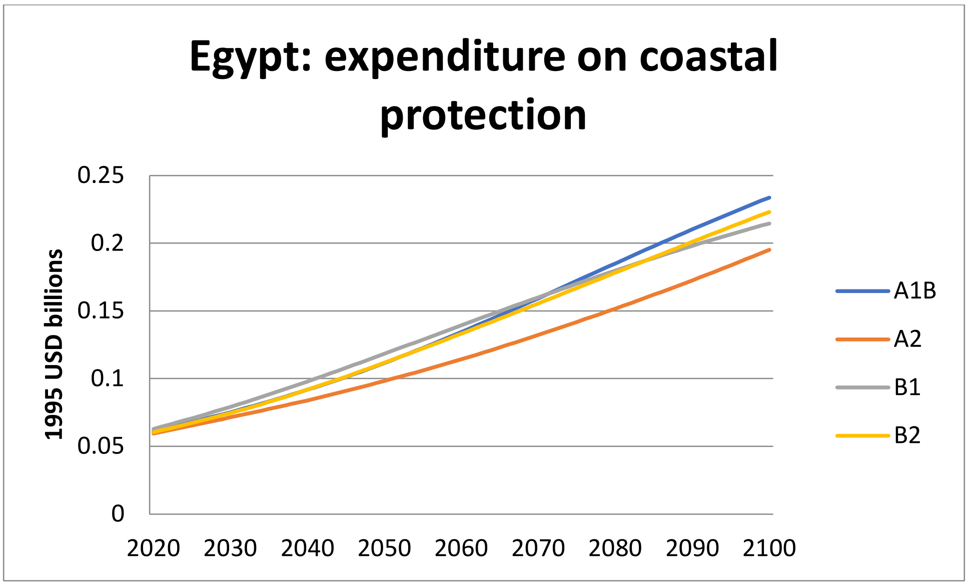



Figure G22: The figure shows the change in Egyptian expenditure on coastal protection as a result of climate change, as estimated by FUND using the regional to national disaggregation process described in Chapter 6. Results are shown between 2020 and 2100, the time span of the FUND case study in Chapter 6. Changes are relative to a baseline in which there are no effects from climate change. Results were run for four SRES scenarios, A1B, A2, B1 and B2, and positive numbers represent increases in expenditure on coastal protection. The results from the different scenarios are shown separately in the figure. The level of coastal protection estimated in FUND was determined by a cost-benefit analysis (CBA) that accounted for the cost of coastal protection and the value of wetland and dryland lost. The cost of coastal protection depended on costs per unit of protection, the extent of sea-level rise (SLR), the rate of pure time preference, and the consumption elasticity of marginal utility. Meanwhile, the value of wetland lost was a function of income per capita, SLR and degree of coastal protection. Finally, the value of dryland lost depended on income per square kilometre and lost land area. Note that an increase in expenditure on coastal protection did not necessarily have a positive effect on the economy, as a budget constraint was imposed, as described in Chapter 6, to ensure that increases in expenditures didn't automatically increase economic growth. An increase in expenditure was thus funded through decreased expenditure on other goods and services, so that government's total spending remained constant.

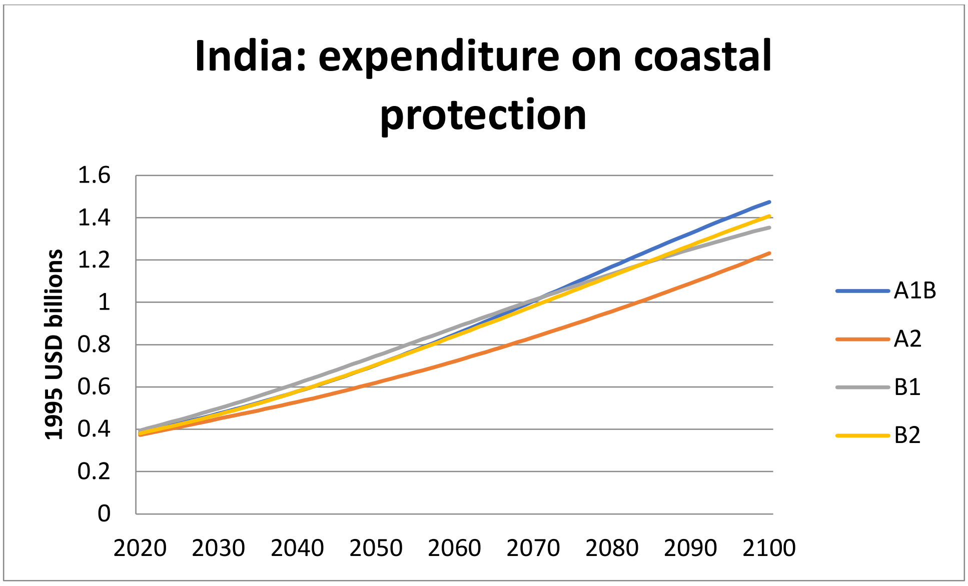



Figure G23: The figure shows the change in Indian expenditure on coastal protection as a result of climate change, as estimated by FUND using the regional to national disaggregation process described in Chapter 6. Results are shown between 2020 and 2100, the time span of the FUND case study in Chapter 6. Changes are relative to a baseline in which there are no effects from climate change. Results were run for four SRES scenarios, A1B, A2, B1 and B2, and positive numbers represent increases in expenditure on coastal protection. The results from the different scenarios are shown separately in the figure. The level of coastal protection estimated in FUND was determined by a cost-benefit analysis (CBA) that accounted for the cost of coastal protection and the value of wetland and dryland lost. The cost of coastal protection depended on costs per unit of protection, the extent of sea-level rise (SLR), the rate of pure time preference, and the consumption elasticity of marginal utility. Meanwhile, the value of wetland lost was a function of income per capita, SLR and degree of coastal protection. Finally, the value of dryland lost depended on income per square kilometre and lost land area. Note that an increase in expenditure on coastal protection did not necessarily have a positive effect on the economy, as a budget constraint was imposed, as described in Chapter 6, to ensure that increases in expenditures didn't automatically increase economic growth. An increase in expenditure was thus funded through decreased expenditure on other goods and services, so that government's total spending remained constant.

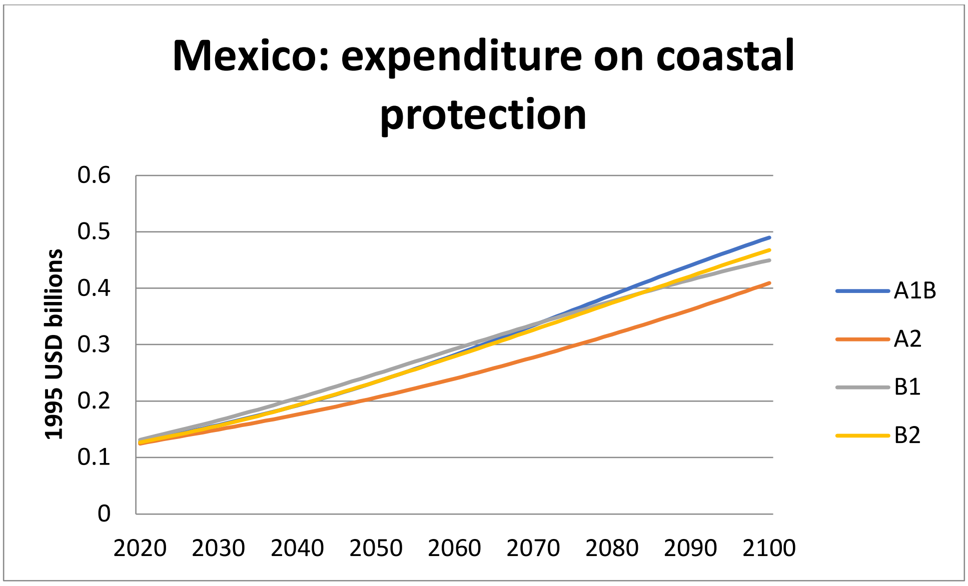



Figure G24: The figure shows the change in Mexican expenditure on coastal protection as a result of climate change, as estimated by FUND using the regional to national disaggregation process described in Chapter 6. Results are shown between 2020 and 2100, the time span of the FUND case study in Chapter 6. Changes are relative to a baseline in which there are no effects from climate change. Results were run for four SRES scenarios, A1B, A2, B1 and B2, and positive numbers represent increases in expenditure on coastal protection. The results from the different scenarios are shown separately in the figure. The level of coastal protection estimated in FUND was determined by a cost-benefit analysis (CBA) that accounted for the cost of coastal protection and the value of wetland and dryland lost. The cost of coastal protection depended on costs per unit of protection, the extent of sea-level rise (SLR), the rate of pure time preference, and the consumption elasticity of marginal utility. Meanwhile, the value of wetland lost was a function of income per capita, SLR and degree of coastal protection. Finally, the value of dryland lost depended on income per square kilometre and lost land area. Note that an increase in expenditure on coastal protection did not necessarily have a positive effect on the economy, as a budget constraint was imposed, as described in Chapter 6, to ensure that increases in expenditures didn't automatically increase economic growth. An increase in expenditure was thus funded through decreased expenditure on other goods and services, so that government's total spending remained constant.

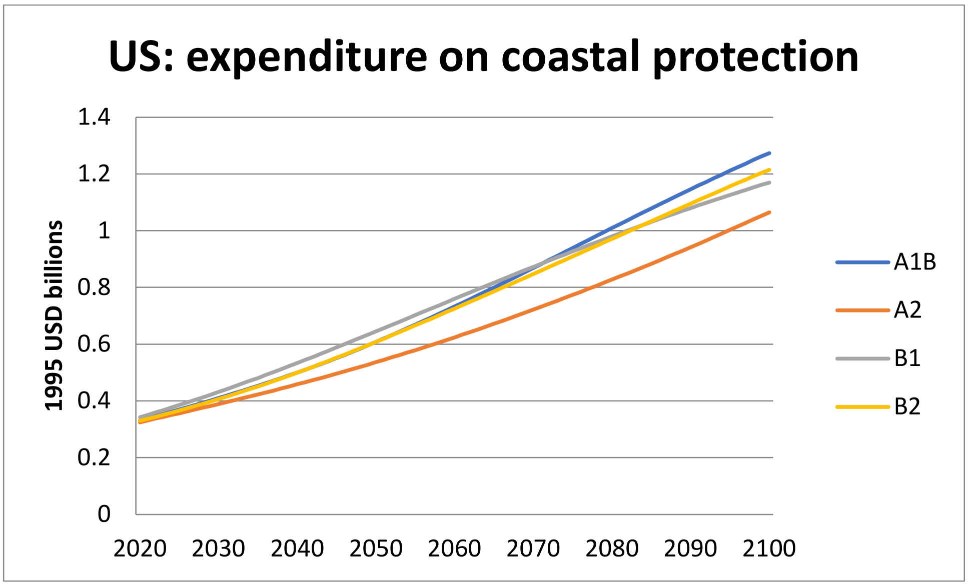



Figure G25: The figure shows the change in American expenditure on coastal protection as a result of climate change, as estimated by FUND, between 2020 and 2100, the time span of the FUND case study in Chapter 6. Changes are relative to a baseline in which there are no effects from climate change. Results were run for four SRES scenarios, A1B, A2, B1 and B2, and positive numbers represent increases in expenditure on coastal protection. The results from the different scenarios are shown separately in the figure. The level of coastal protection estimated in FUND was determined by a cost-benefit analysis (CBA) that accounted for the cost of coastal protection and the value of wetland and dryland lost. The cost of coastal protection depended on costs per unit of protection, the extent of sea-level rise (SLR), the rate of pure time preference, and the consumption elasticity of marginal utility. Meanwhile, the value of wetland lost was a function of income per capita, SLR and degree of coastal protection. Finally, the value of dryland lost depended on income per square kilometre and lost land area. Note that an increase in expenditure on coastal protection did not necessarily have a positive effect on the economy, as a budget constraint was imposed, as described in Chapter 6, to ensure that increases in expenditures didn't automatically increase economic growth. An increase in expenditure was thus funded through decreased expenditure on other goods and services, so that government's total spending remained constant.

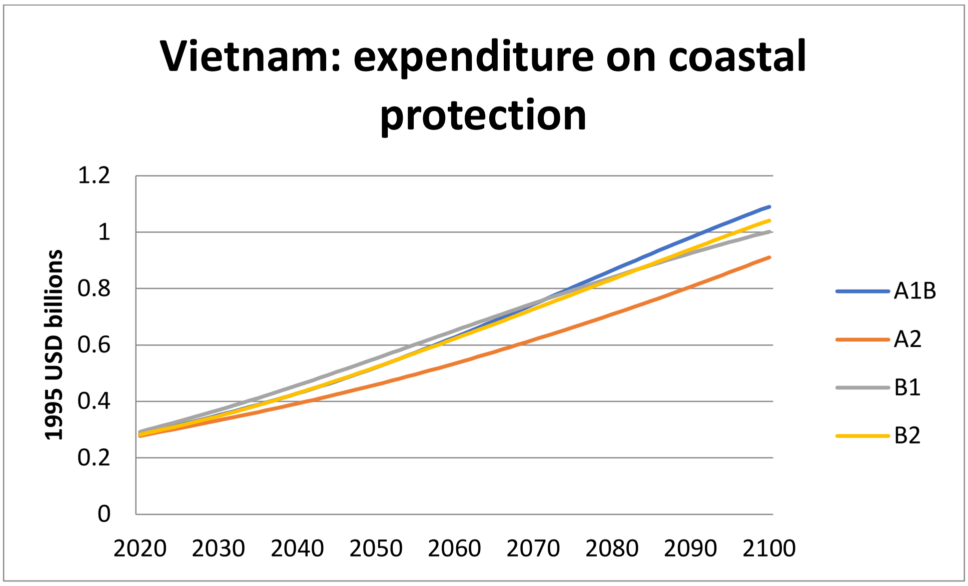


Figure G26: The figure shows the change in Vietnamese expenditure on coastal protection as a result of climate change, as estimated by FUND using the regional to national disaggregation process described in Chapter 6. Results are shown between 2020 and 2100, the time span of the FUND case study in Chapter 6. Changes are relative to a baseline in which there are no effects from climate change. Results were run for four SRES scenarios, A1B, A2, B1 and B2, and positive numbers represent increases in expenditure on coastal protection. The results from the different scenarios are shown separately in the figure. The level of coastal protection estimated in FUND was determined by a cost-benefit analysis (CBA) that accounted for the cost of coastal protection and the value of wetland and dryland lost. The cost of coastal protection depended on costs per unit of protection, the extent of sea-level rise (SLR), the rate of pure time preference, and the consumption elasticity of marginal utility. Meanwhile, the value of wetland lost was a function of income per capita, SLR and degree of coastal protection. Finally, the value of dryland lost depended on income per square kilometre and lost land area. Note that an increase in expenditure on coastal protection did not necessarily have a positive effect on the economy, as a budget constraint was imposed, as described in Chapter 6, to ensure that increases in expenditures didn't automatically increase economic growth. An increase in expenditure was thus funded through decreased expenditure on other goods and services, so that government's total spending remained constant.

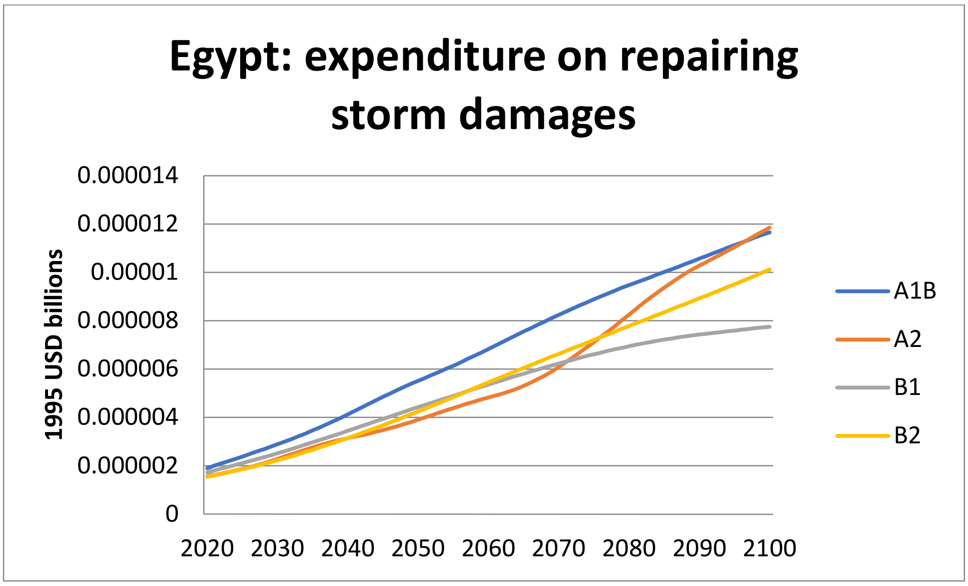



Figure G27: The figure shows the change in Egyptian expenditure on repairing damages from tropical and extra-tropical storms as a result of climate change, as estimated by FUND using the regional to national disaggregation process described in Chapter 6. Results are shown between 2020 and 2100, the time span of the FUND case study in Chapter 6. Changes are relative to a baseline in which there are no effects from climate change. Results were run for four SRES scenarios, A1B, A2, B1 and B2, and positive numbers represent increases in expenditure on storm repairs. The results from the different scenarios are shown separately in the figure. FUND's economic damages from tropical storms impact function is dependent on the increase in regional income per capita and temperature, while FUND's economic damages from extratropical storms impact function is dependent on regional income per capita and atmospheric $CO_2$ concentration. Damages from tropical and extratropical storms were summed and so taken collectively in the FUND case study. Note that an increase in expenditure on storm repairs did not necessarily have a positive effect on the economy, as a budget constraint was imposed, as described in Chapter 6, to ensure that increases in expenditures didn't automatically increase economic growth. An increase in expenditure was thus funded through decreased expenditure on other goods and services, so that household, enterprise and government's total investment spending remained constant.

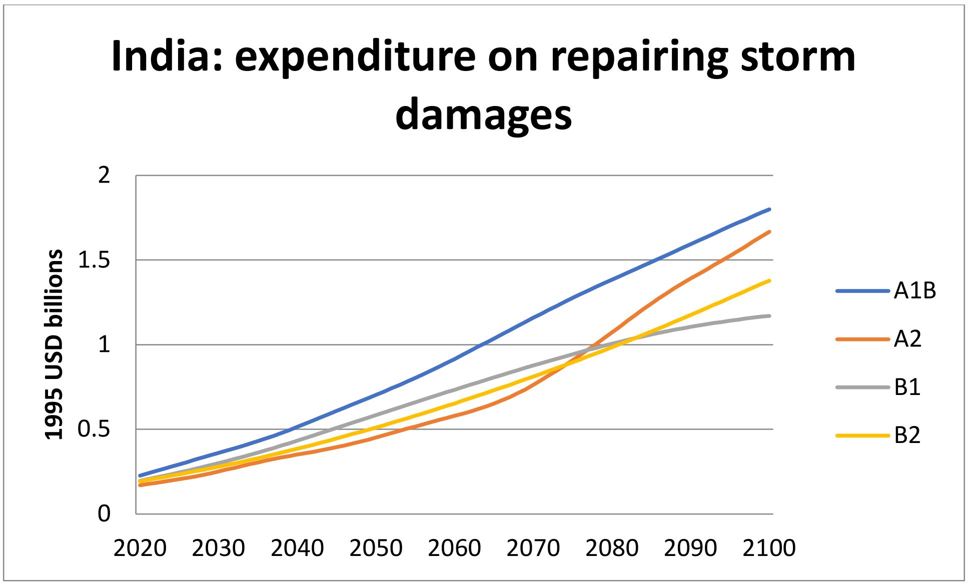



Figure G28: The figure shows the change in Indian expenditure on repairing damages from tropical and extra-tropical storms as a result of climate change, as estimated by FUND using the regional to national disaggregation process described in Chapter 6. Results are shown between 2020 and 2100, the time span of the FUND case study in Chapter 6. Changes are relative to a baseline in which there are no effects from climate change. Results were run for four SRES scenarios, A1B, A2, B1 and B2, and positive numbers represent increases in expenditure on storm repairs. The results from the different scenarios are shown separately in the figure. FUND's economic damages from tropical storms impact function is dependent on the increase in regional income per capita and temperature, while FUND's economic damages from extratropical storms impact function is dependent on regional income per capita and atmospheric $CO_2$ concentration. Damages from tropical and extratropical storms were summed and so taken collectively in the FUND case study. Note that an increase in expenditure on storm repairs did not necessarily have a positive effect on the economy, as a budget constraint was imposed, as described in Chapter 6, to ensure that increases in expenditures didn't automatically increase economic growth. An increase in expenditure was thus funded through decreased expenditure on other goods and services, so that household, enterprise and government's total investment spending remained constant.

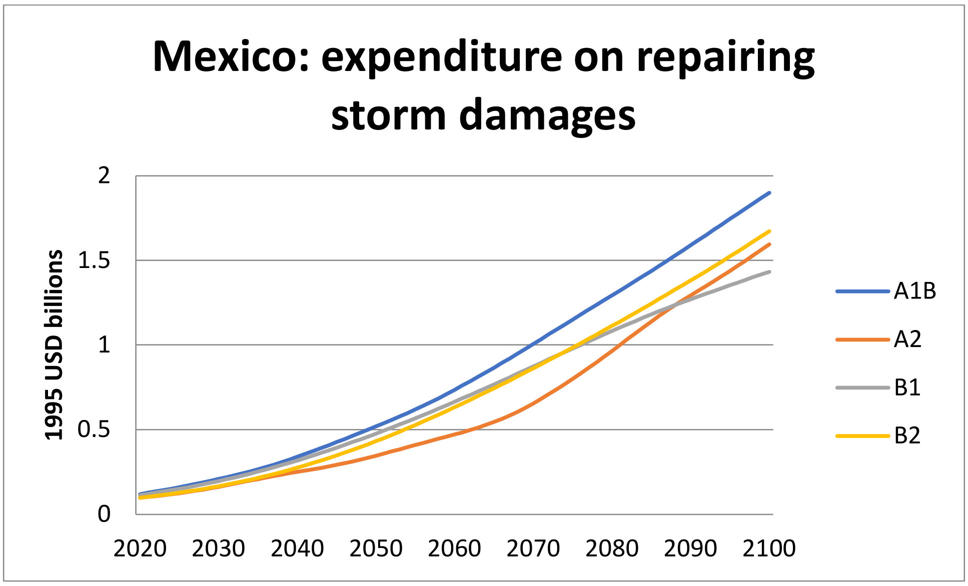



Figure G29: The figure shows the change in Mexican expenditure on repairing damages from tropical and extra-tropical storms as a result of climate change, as estimated by FUND using the regional to national disaggregation process described in Chapter 6. Results are shown between 2020 and 2100, the time span of the FUND case study in Chapter 6. Changes are relative to a baseline in which there are no effects from climate change. Results were run for four SRES scenarios, A1B, A2, B1 and B2, and positive numbers represent increases in expenditure on storm repairs. The results from the different scenarios are shown separately in the figure. FUND's economic damages from tropical storms impact function is dependent on the increase in regional income per capita and temperature, while FUND's economic damages from extratropical storms impact function is dependent on regional income per capita and atmospheric $CO_2$ concentration. Damages from tropical and extratropical storms were summed and so taken collectively in the FUND case study. Note that an increase in expenditure on storm repairs did not necessarily have a positive effect on the economy, as a budget constraint was imposed, as described in Chapter 6, to ensure that increases in expenditures didn't automatically increase economic growth. An increase in expenditure was thus funded through decreased expenditure on other goods and services, so that household, enterprise and government's total investment spending remained constant.

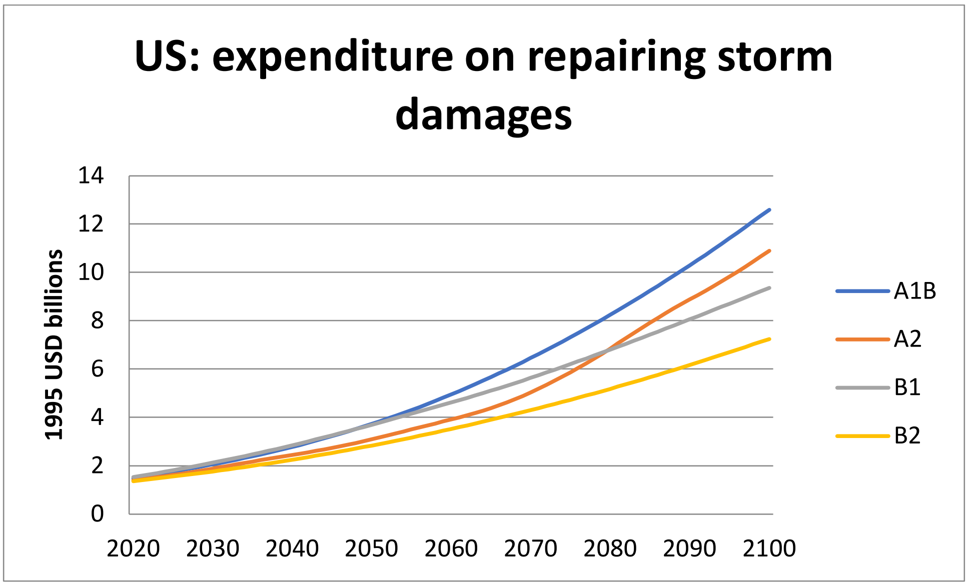



Figure G30: The figure shows the change in American expenditure on repairing damages from tropical and extra-tropical storms as a result of climate change, as estimated by FUND, between 2020 and 2100, the time span of the FUND case study in Chapter 6. Changes are relative to a baseline in which there are no effects from climate change. Results were run for four SRES scenarios, A1B, A2, B1 and B2, and positive numbers represent increases in expenditure on storm repairs. The results from the different scenarios are shown separately in the figure. FUND's economic damages from tropical storms impact function is dependent on the increase in regional income per capita and temperature, while FUND's economic damages from extratropical storms impact function is dependent on regional income per capita and atmospheric $CO_2$ concentration. Damages from tropical and extratropical storms were summed and so taken collectively in the FUND case study. Note that an increase in expenditure on storm repairs did not necessarily have a positive effect on the economy, as a budget constraint was imposed, as described in Chapter 6, to ensure that increases in expenditures didn't automatically increase economic growth. An increase in expenditure was thus funded through decreased expenditure on other goods and services, so that household, enterprise and government's total investment spending remained constant.

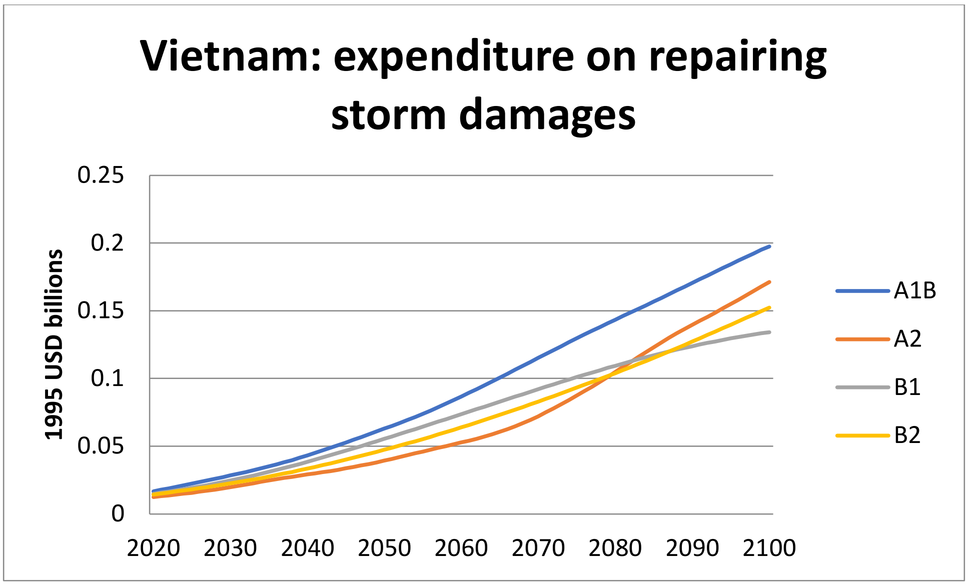



Figure G31: The figure shows the change in Vietnamese expenditure on repairing damages from tropical and extra-tropical storms as a result of climate change, as estimated by FUND using the regional to national disaggregation process described in Chapter 6. Results are shown between 2020 and 2100, the time span of the FUND case study in Chapter 6. Changes are relative to a baseline in which there are no effects from climate change. Results were run for four SRES scenarios, A1B, A2, B1 and B2, and positive numbers represent increases in expenditure on storm repairs. The results from the different scenarios are shown separately in the figure. FUND's economic damages from tropical storms impact function is dependent on the increase in regional income per capita and temperature, while FUND's economic damages from extratropical storms impact function is dependent on regional income per capita and atmospheric $CO_2$ concentration. Damages from tropical and extratropical storms were summed and so taken collectively in the FUND case study. Note that an increase in expenditure on storm repairs did not necessarily have a positive effect on the economy, as a budget constraint was imposed, as described in Chapter 6, to ensure that increases in expenditures didn't automatically increase economic growth. An increase in expenditure was thus funded through decreased expenditure on other goods and services, so that household, enterprise and government's total investment spending remained constant.

# Appendix H – Breakdown of impacts from unit exogenous changes into direct and indirect effects

## Alaska

| Sector with unit exogenous change | Inequality ratio | Change in inequality ratio due to direct effects | Change in inequality ratio due to indirect effects | Change in inequality ratio due to total effects | Percentage of total change in inequality ratio that is down to direct effects | Percentage of total change in inequality ratio that is down to indirect effects |
|---|---|---|---|---|---|---|
| Infrastructure | H/L | 3.06% | -1.04% | 2.0% | 152% | -52% |
| Infrastructure | H/M | 2.00% | -0.50% | 1.5% | 134% | -34% |
| Infrastructure | M/L | 1.04% | -0.53% | 0.5% | 203% | -103% |
| Tourism | H/L | -0.12% | 0.75% | 0.6% | -19% | 119% |
| Tourism | H/M | -1.03% | 0.01% | -1.0% | 101% | -1% |
| Tourism | M/L | 0.92% | 0.75% | 1.7% | 55% | 45% |
| Oil | H/L | 1.25% | 0.86% | 2.1% | 59% | 41% |
| Oil | H/M | 0.59% | 0.11% | 0.7% | 84% | 16% |
| Oil | M/L | 0.66% | 0.74% | 1.4% | 47% | 53% |
| Fisheries | H/L | -0.09% | 3.23% | 3.1% | -3% | 103% |
| Fisheries | H/M | -0.24% | 2.42% | 2.2% | -11% | 111% |
| Fisheries | M/L | 0.15% | 0.79% | 0.9% | 16% | 84% |

Table H1: Table shows how the effects on Alaskan inequality ratios of increases of USD 1 billion (in 1995 USD billions) in, each in turn, expenditure on infrastructure, increased tourism, oil output, and fisheries output, are broken down into direct and indirect effects. Total effects were taken from Figure 8.4 in Chapter 8, and direct, indirect and total effects were calculated as described in Section 8.1.1 of Chapter 8. Total effects are defined to be direct plus indirect effects. H represents the total income of high income households (households earning more than $75,000 a year, in 2008 USD), M represents the total income of medium income households (households earning between $25,000 and $75,000 a year, in 2008 USD), and L represents the total income of low income households (households earning less than $25,000 a year, in 2008 USD).

# Egypt

| Sector with unit exogenous change | Inequality ratio | Change in inequality ratio due to direct effects | Change in inequality ratio due to indirect effects | Change in inequality ratio due to total effects | Percentage of total change in inequality ratio that is down to direct effects | Percentage of total change in inequality ratio that is down to indirect effects |
|---|---|---|---|---|---|---|
| Agriculture | Q5/Q1 | -0.20% | 0.10% | -0.10% | 195% | -95% |
| Agriculture | Q5/Q3 | -0.12% | 0.06% | -0.06% | 199% | -99% |
| Agriculture | Q3/Q1 | -0.08% | 0.04% | -0.04% | 190% | -90% |
| Agriculture | (Q4+Q5)/(Q1+Q2) | -0.15% | 0.06% | -0.08% | 178% | -78% |
| Water | Q5/Q1 | -0.12% | 0.04% | -0.08% | 151% | -51% |
| Water | Q5/Q3 | -0.09% | 0.02% | -0.08% | 123% | -23% |
| Water | Q3/Q1 | -0.03% | 0.02% | 0.00% | 611% | -511% |
| Water | (Q4+Q5)/(Q1+Q2) | -0.09% | 0.02% | -0.07% | 135% | -35% |
| Energy | Q5/Q1 | -0.01% | 0.06% | 0.05% | -23% | 123% |
| Energy | Q5/Q3 | -0.01% | 0.03% | 0.02% | -59% | 159% |
| Energy | Q3/Q1 | 0.00% | 0.02% | 0.02% | 7% | 93% |
| Energy | (Q4+Q5)/(Q1+Q2) | -0.01% | 0.04% | 0.03% | -28% | 128% |
| SLR | Q5/Q1 | -0.13% | 0.00% | -0.12% | 104% | -4% |
| SLR | Q5/Q3 | -0.09% | 0.03% | -0.06% | 143% | -43% |
| SLR | Q3/Q1 | -0.04% | -0.02% | -0.06% | 68% | 32% |
| SLR | (Q4+Q5)/(Q1+Q2) | -0.10% | 0.00% | -0.10% | 101% | -1% |
| Storms | Q5/Q1 | -0.13% | 0.03% | -0.10% | 133% | -33% |
| Storms | Q5/Q3 | -0.09% | 0.02% | -0.07% | 128% | -28% |
| Storms | Q3/Q1 | -0.04% | 0.01% | -0.03% | 143% | -43% |
| Storms | (Q4+Q5)/(Q1+Q2) | -0.10% | 0.02% | -0.08% | 127% | -27% |

Table H2: Table shows how the effects on Egyptian inequality ratios of increases of USD 1 billion (in 1995 USD billions) in, each in turn, agricultural output, water output, energy expenditure, expenditure on coastal defence, and expenditure on repairing storm damages, are broken down into direct and indirect effects. Total effects were taken from Figure 8.3 in Chapter 8, and direct, indirect and total effects were calculated as described in Section 8.1.1 of Chapter 8. Total effects are defined to be direct plus indirect effects. Q1 represents the income of the lowest expenditure quintile, while Q5 represents the income of highest expenditure quintile.

## Ethiopia

| Sector with unit exogenous change | Inequality ratio | Change in inequality ratio due to direct effects | Change in inequality ratio due to indirect effects | Change in inequality ratio due to total effects | Percentage of total change in inequality ratio that is down to direct effects | Percentage of total change in inequality ratio that is down to indirect effects |
|---|---|---|---|---|---|---|
| Agriculture | Q5/Q1 | -2.29% | -1.41% | -3.7% | 62% | 38% |
| Agriculture | Q5/Q3 | -1.66% | -1.00% | -2.7% | 63% | 37% |
| Agriculture | Q3/Q1 | -0.63% | -0.43% | -1.1% | 59% | 41% |
| Agriculture | (Q4+Q5)/(Q1+Q2) | -1.73% | -1.09% | -2.8% | 61% | 39% |
| Water | Q5/Q1 | 0.12% | 2.59% | 2.7% | 4% | 96% |
| Water | Q5/Q3 | 0.09% | 1.80% | 1.9% | 5% | 95% |
| Water | Q3/Q1 | 0.03% | 0.77% | 0.8% | 4% | 96% |
| Water | (Q4+Q5)/(Q1+Q2) | 0.10% | 1.96% | 2.1% | 5% | 95% |
| Energy | Q5/Q1 | 0.20% | 1.84% | 2.0% | 10% | 90% |
| Energy | Q5/Q3 | 0.15% | 1.29% | 1.4% | 10% | 90% |
| Energy | Q3/Q1 | 0.05% | 0.54% | 0.6% | 9% | 91% |
| Energy | (Q4+Q5)/(Q1+Q2) | 0.17% | 1.40% | 1.6% | 11% | 89% |
| Storms | Q5/Q1 | 0.00% | 1.23% | 1.2% | 0% | 100% |
| Storms | Q5/Q3 | 0.00% | 0.86% | 0.9% | 1% | 99% |
| Storms | Q3/Q1 | 0.00% | 0.37% | 0.4% | -1% | 101% |
| Storms | (Q4+Q5)/(Q1+Q2) | 0.02% | 0.93% | 0.9% | 2% | 98% |

Table H3: Table shows how the effects on Ethiopian inequality ratios of increases of USD 1 billion (in 1995 USD billions) in, each in turn, agricultural output, water output, energy expenditure, and expenditure on repairing storm damages, are broken down into direct and indirect effects. Total effects were taken from Figure 8.3 in Chapter 8, and direct, indirect and total effects were calculated as described in Section 8.1.1 of Chapter 8. Total effects are defined to be direct plus indirect effects. Q1 represents the income of the lowest expenditure quintile, while Q5 represents the income of highest expenditure quintile.

# India

| Sector with unit exogenous change | Inequality ratio | Change in inequality ratio due to direct effects | Change in inequality ratio due to indirect effects | Change in inequality ratio due to total effects | Percentage of total change in inequality ratio that is down to direct effects | Percentage of total change in inequality ratio that is down to indirect effects |
|---|---|---|---|---|---|---|
| Agriculture | Q5/Q1 | -0.05% | 0.03% | -0.02% | 244% | -144% |
| Agriculture | Q5/Q3 | -0.03% | 0.02% | -0.01% | 251% | -151% |
| Agriculture | Q3/Q1 | -0.02% | 0.01% | -0.01% | 237% | -137% |
| Agriculture | (Q4+Q5)/(Q1+Q2) | -0.04% | 0.02% | -0.02% | 249% | -149% |
| Water | Q5/Q1 | 0.01% | 0.02% | 0.04% | 37% | 63% |
| Water | Q5/Q3 | 0.00% | 0.01% | 0.01% | -5% | 105% |
| Water | Q3/Q1 | 0.01% | 0.01% | 0.03% | 55% | 45% |
| Water | (Q4+Q5)/(Q1+Q2) | 0.01% | 0.02% | 0.03% | 34% | 66% |
| Energy | Q5/Q1 | -0.04% | -0.01% | -0.05% | 79% | 21% |
| Energy | Q5/Q3 | -0.02% | 0.00% | -0.02% | 82% | 18% |
| Energy | Q3/Q1 | -0.02% | -0.01% | -0.02% | 76% | 24% |
| Energy | (Q4+Q5)/(Q1+Q2) | -0.03% | -0.01% | -0.03% | 80% | 20% |
| SLR | Q5/Q1 | -0.05% | 0.00% | -0.05% | 104% | -4% |
| SLR | Q5/Q3 | -0.03% | 0.00% | -0.03% | 93% | 7% |
| SLR | Q3/Q1 | -0.02% | 0.00% | -0.02% | 121% | -21% |
| SLR | (Q4+Q5)/(Q1+Q2) | -0.03% | 0.00% | -0.03% | 108% | -8% |
| Storms | Q5/Q1 | -0.05% | -0.01% | -0.05% | 90% | 10% |
| Storms | Q5/Q3 | -0.03% | 0.00% | -0.03% | 89% | 11% |
| Storms | Q3/Q1 | -0.02% | 0.00% | -0.02% | 91% | 9% |
| Storms | (Q4+Q5)/(Q1+Q2) | -0.03% | 0.00% | -0.04% | 90% | 10% |

Table H4: Table shows how the effects on Indian inequality ratios of increases of USD 1 billion (in 1995 USD billions) in, each in turn, agricultural output, water output, energy expenditure, expenditure on coastal defence, and expenditure on repairing storm damages, are broken down into direct and indirect effects. Total effects were taken from Figure 8.3 in Chapter 8, and direct, indirect and total effects were calculated as described in Section 8.1.1 of Chapter 8. Total effects are defined to be direct plus indirect effects. Q1 represents the income of the lowest expenditure quintile, while Q5 represents the income of highest expenditure quintile.

## Mexico

| Sector with unit exogenous change | Inequality ratio | Change in inequality ratio due to direct effects | Change in inequality ratio due to indirect effects | Change in inequality ratio due to total effects | Percentage of total change in inequality ratio that is down to direct effects | Percentage of total change in inequality ratio that is down to indirect effects |
|---|---|---|---|---|---|---|
| Agriculture | Q5/Q1 | -0.04% | 0.07% | 0.03% | -119% | 219% |
| Agriculture | Q5/Q3 | -0.03% | 0.06% | 0.03% | -89% | 189% |
| Agriculture | Q3/Q1 | -0.01% | 0.01% | 0.00% | -498% | 598% |
| Agriculture | (Q4+Q5)/(Q1+Q2) | -0.03% | 0.06% | 0.03% | -118% | 218% |
| Water | Q5/Q1 | 0.00% | 0.06% | 0.05% | -8% | 108% |
| Water | Q5/Q3 | -0.01% | 0.05% | 0.04% | -26% | 126% |
| Water | Q3/Q1 | 0.01% | 0.01% | 0.02% | 30% | 70% |
| Water | (Q4+Q5)/(Q1+Q2) | 0.00% | 0.04% | 0.04% | -11% | 111% |
| Energy | Q5/Q1 | 0.00% | 0.04% | 0.04% | -12% | 112% |
| Energy | Q5/Q3 | -0.01% | 0.04% | 0.03% | -28% | 128% |
| Energy | Q3/Q1 | 0.01% | 0.00% | 0.00% | 296% | -196% |
| Energy | (Q4+Q5)/(Q1+Q2) | 0.00% | 0.03% | 0.03% | -16% | 116% |
| SLR | Q5/Q1 | -0.06% | -0.02% | -0.07% | 75% | 25% |
| SLR | Q5/Q3 | -0.05% | 0.02% | -0.02% | 219% | -119% |
| SLR | Q3/Q1 | -0.01% | -0.04% | -0.05% | 19% | 81% |
| SLR | (Q4+Q5)/(Q1+Q2) | -0.05% | -0.01% | -0.06% | 76% | 24% |
| Storms | Q5/Q1 | -0.06% | 0.02% | -0.03% | 178% | -78% |
| Storms | Q5/Q3 | -0.05% | 0.03% | -0.02% | 236% | -136% |
| Storms | Q3/Q1 | -0.01% | 0.00% | -0.01% | 86% | 14% |
| Storms | (Q4+Q5)/(Q1+Q2) | -0.05% | 0.02% | -0.03% | 176% | -76% |

Table H5: Table shows how the effects on Mexican inequality ratios of increases of USD 1 billion (in 1995 USD billions) in, each in turn, agricultural output, water output, energy expenditure, expenditure on coastal defence, and expenditure on repairing storm damages, are broken down into direct and indirect effects. Total effects were taken from Figure 8.3 in Chapter 8, and direct, indirect and total effects were calculated as described in Section 8.1.1 of Chapter 8. Total effects are defined to be direct plus indirect effects. Q1 represents the income of the lowest income quintile, while Q5 represents the income of highest income quintile.

## United States (US)

| Sector with unit exogenous change | Inequality ratio | Change in inequality ratio due to direct effects | Change in inequality ratio due to indirect effects | Change in inequality ratio due to total effects | Percentage of total change in inequality ratio that is down to direct effects | Percentage of total change in inequality ratio that is down to indirect effects |
|---|---|---|---|---|---|---|
| Agriculture | Q5/Q1 | -0.0005% | 0.0043% | 0.004% | -13.5% | 113.5% |
| Agriculture | Q5/Q3 | -0.0005% | 0.0021% | 0.002% | -31.9% | 131.9% |
| Agriculture | Q3/Q1 | 0.0000% | 0.0022% | 0.002% | -0.1% | 100.1% |
| Agriculture | (Q4+Q5)/(Q1+Q2) | -0.0004% | 0.0027% | 0.002% | -15.2% | 115.2% |
| Water | Q5/Q1 | 0.0014% | 0.0058% | 0.007% | 19.9% | 80.1% |
| Water | Q5/Q3 | 0.0011% | 0.0030% | 0.004% | 27.2% | 72.8% |
| Water | Q3/Q1 | 0.0003% | 0.0029% | 0.003% | 10.7% | 89.3% |
| Water | (Q4+Q5)/(Q1+Q2) | 0.0013% | 0.0042% | 0.005% | 22.9% | 77.1% |
| Energy | Q5/Q1 | 0.0014% | -0.0012% | 0.000% | 617.5% | -517.5% |
| Energy | Q5/Q3 | 0.0011% | -0.0008% | 0.000% | 430.3% | -330.3% |
| Energy | Q3/Q1 | 0.0003% | -0.0004% | 0.000% | -1563.9% | 1663.9% |
| Energy | (Q4+Q5)/(Q1+Q2) | 0.0013% | -0.0011% | 0.000% | 822.3% | -722.3% |
| SLR | Q5/Q1 | 0.0012% | -0.0048% | -0.004% | -33.0% | 133.0% |
| SLR | Q5/Q3 | -0.0008% | -0.0017% | -0.003% | 32.4% | 67.6% |
| SLR | Q3/Q1 | 0.0020% | -0.0031% | -0.001% | -180.4% | 280.4% |
| SLR | (Q4+Q5)/(Q1+Q2) | 0.0009% | -0.0037% | -0.003% | -32.7% | 132.7% |
| Storms | Q5/Q1 | 0.0012% | -0.0015% | 0.000% | -434.6% | 534.6% |
| Storms | Q5/Q3 | -0.0008% | -0.0012% | -0.002% | 41.2% | 58.8% |
| Storms | Q3/Q1 | 0.0020% | -0.0003% | 0.002% | 118.2% | -18.2% |
| Storms | (Q4+Q5)/(Q1+Q2) | 0.0009% | -0.0013% | 0.000% | -208.8% | 308.8% |

Table H6: Table shows how the effects on American inequality ratios of increases of USD 1 billion (in 1995 USD billions) in, each in turn, agricultural output, water output, energy expenditure, expenditure on coastal defence, and expenditure on repairing storm damages, are broken down into direct and indirect effects. Total effects were taken from Figure 8.3 in Chapter 8, and direct, indirect and total effects were calculated as described in Section 8.1.1 of Chapter 8. Total effects are defined to be direct plus indirect effects. Q1 represents the income of the lowest income quintile, while Q5 represents the income of highest income quintile.

## Vietnam

| Sector with unit exogenous change | Inequality ratio | Change in inequality ratio due to direct effects | Change in inequality ratio due to indirect effects | Change in inequality ratio due to total effects | Percentage of total change in inequality ratio that is down to direct effects | Percentage of total change in inequality ratio that is down to indirect effects |
|---|---|---|---|---|---|---|
| Agriculture | Q5/Q1 | -0.74% | -0.77% | -1.5% | 49% | 51% |
| Agriculture | Q5/Q3 | -0.41% | -0.41% | -0.8% | 50% | 50% |
| Agriculture | Q3/Q1 | -0.32% | -0.36% | -0.7% | 47% | 53% |
| Agriculture | (Q4+Q5)/(Q1+Q2) | -0.57% | -0.59% | -1.2% | 49% | 51% |
| Water | Q5/Q1 | 0.44% | 0.31% | 0.7% | 58% | 42% |
| Water | Q5/Q3 | 0.31% | 0.14% | 0.4% | 69% | 31% |
| Water | Q3/Q1 | 0.12% | 0.18% | 0.3% | 41% | 59% |
| Water | (Q4+Q5)/(Q1+Q2) | 0.36% | 0.25% | 0.6% | 59% | 41% |
| Energy | Q5/Q1 | 0.39% | 0.35% | 0.7% | 52% | 48% |
| Energy | Q5/Q3 | 0.22% | 0.19% | 0.4% | 54% | 46% |
| Energy | Q3/Q1 | 0.16% | 0.16% | 0.3% | 50% | 50% |
| Energy | (Q4+Q5)/(Q1+Q2) | 0.31% | 0.27% | 0.6% | 53% | 47% |
| SLR | Q5/Q1 | -0.41% | -0.98% | -1.4% | 30% | 70% |
| SLR | Q5/Q3 | -0.30% | -0.53% | -0.8% | 37% | 63% |
| SLR | Q3/Q1 | -0.11% | -0.46% | -0.6% | 19% | 81% |
| SLR | (Q4+Q5)/(Q1+Q2) | -0.32% | -0.78% | -1.1% | 29% | 71% |
| Storms | Q5/Q1 | -0.41% | 0.08% | -0.3% | 125% | -25% |
| Storms | Q5/Q3 | -0.30% | 0.04% | -0.3% | 117% | -17% |
| Storms | Q3/Q1 | -0.11% | 0.04% | -0.1% | 155% | -55% |
| Storms | (Q4+Q5)/(Q1+Q2) | -0.32% | 0.06% | -0.3% | 126% | -26% |

Table H7: Table shows how the effects on Vietnamese inequality ratios of increases of USD 1 billion (in 1995 USD billions) in, each in turn, agricultural output, water output, energy expenditure, expenditure on coastal defence, and expenditure on repairing storm damages, are broken down into direct and indirect effects. Total effects were taken from Figure 8.3 in Chapter 8, and direct, indirect and total effects were calculated as described in Section 8.1.1 of Chapter 8. Total effects are defined to be direct plus indirect effects. Q1 represents the income of the lowest expenditure quintile, while Q5 represents the income of highest expenditure quintile.

## Zambia

| Sector with unit exogenous change | Inequality ratio | Change in inequality ratio due to direct effects | Change in inequality ratio due to indirect effects | Change in inequality ratio due to total effects | Percentage of total change in inequality ratio that is down to direct effects | Percentage of total change in inequality ratio that is down to indirect effects |
|---|---|---|---|---|---|---|
| Agriculture | Q5/Q1 | -2.23% | -0.05627 | -7.9% | 28% | 72% |
| Agriculture | Q5/Q3 | -1.74% | -0.04434 | -6.2% | 28% | 72% |
| Agriculture | Q3/Q1 | -0.50% | -0.01295 | -1.8% | 28% | 72% |
| Agriculture | (Q4+Q5)/(Q1+Q2) | -1.87% | -0.05125 | -7.0% | 27% | 73% |
| Water | Q5/Q1 | 2.02% | 0.030498 | 5.1% | 40% | 60% |
| Water | Q5/Q3 | 1.38% | 0.017817 | 3.2% | 44% | 56% |
| Water | Q3/Q1 | 0.63% | 0.012184 | 1.9% | 34% | 66% |
| Water | (Q4+Q5)/(Q1+Q2) | 1.72% | 0.025526 | 4.3% | 40% | 60% |
| Energy | Q5/Q1 | 1.88% | 0.024815 | 4.4% | 43% | 57% |
| Energy | Q5/Q3 | 1.29% | 0.014909 | 2.8% | 46% | 54% |
| Energy | Q3/Q1 | 0.59% | 0.009553 | 1.5% | 38% | 62% |
| Energy | (Q4+Q5)/(Q1+Q2) | 1.60% | 0.020836 | 3.7% | 43% | 57% |
| Storms | Q5/Q1 | 0.55% | 0.014647 | 2.0% | 27% | 73% |
| Storms | Q5/Q3 | 0.26% | 0.007859 | 1.0% | 25% | 75% |
| Storms | Q3/Q1 | 0.28% | 0.006696 | 1.0% | 30% | 70% |
| Storms | (Q4+Q5)/(Q1+Q2) | 0.45% | 0.012224 | 1.7% | 27% | 73% |

Table H8: Table shows how the effects on Zambian inequality ratios of increases of USD 1 billion (in 1995 USD billions) in, each in turn, agricultural output, water output, energy expenditure, and expenditure on repairing storm damages, are broken down into direct and indirect effects. Total effects were taken from Figure 8.3 in Chapter 8, and direct, indirect and total effects were calculated as described in Section 8.1.1 of Chapter 8. Total effects are defined to be direct plus indirect effects. Q1 represents the income of the lowest expenditure quintile, while Q5 represents the income of highest expenditure quintile.

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